THREE ESSAYS ON THE INTERRELATIONSHIPS AMONG CLIMATE, CONFLICT AND ECONOMICS

A Dissertation

by

JUNYI CHEN

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Chair of Committee,	Bruce A. McCarl
Co-Chair of Committee,	Edwin C. Price
Committee Members,	David A. Bessler
	Ximing Wu
	Keli Xu
Head of Department,	C. Parr Rosson III

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ABSTRACT

Conflict in a country is socially expensive and many are trying to understand what factors stimulate it in an effort to figure out ways to lessen its incidence. In this work three essays are presented on factors that drive conflict. The factors examined are: 1) the interrelationship between climate and conflict, 2) the causality between commodity prices and conflict, 3) the ways cereal demand affects and is affected by terrorism.

In the first essay, we use a global dataset to econometrically explore whether the probability of conflict is affected by climate. We find that precipitation variation does have a statistically significant effect. That is, the less precipitation this year relative to the last, the more likely the country is to suffer from civil conflict. Methodologically the best predictions are obtained from a semiparametric estimation technique.

In the second essay, we econometrically investigate the dynamic relationship between commodity prices and the onset of conflict in Sudan. Applying Structure Vector Autoregression (SVAR) and Linear Non-Gaussian Acyclic Model (LiNGAM), we find that wheat price is a cause of conflict events in Sudan. However, we find no feedback from conflict to commodity prices.

In the third essay, we examine the extent that demand for three main cereals in Sudan (sorghum, millet, and wheat) is altered by the incidence of terrorism plus the effect of terrorism events on cereal demand. This is done by using an Almost Ideal Demand System (AIDS) and a Directed Acyclic Graph (DAG) approach. The results show terrorist attacks do cause changes in commodity demand for wheat. The DAG analysis also tentatively suggests that wheat demand is both marginally affected by and directly affecting the incidence of terrorism (conflict) in Sudan. Subsequently, we generate forecasts for the three commodities shares with the AIDS and DAG models, incorporating the effects of terrorist attacks. Examining those results independently and jointly, we find that a composite forecast of the two generates better forecasts.

DEDICATION

To my dear family

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All work for the dissertation was completed by the student, under the guidance of the dissertation committee mentioned above with additional advice received from Dr. Shahriar Kibriya in the Center on Conflict and Development of the Department of Agricultural Economics.

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Its contents are solely the responsibility of the author and do not necessarily represent the official views of any of the organizations mentioned above.

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NOMENCLATURE

ACLED	Armed Conflict Location & Event Dataset
ADF	Augmented Dickey-Fuller
AIDS	Almost Ideal Demand System
AME	Average Marginal Effects
CRED	Centre for Research on the Epidemiology of Disasters
DAG	Directed Acyclic Graph
EM-DAT	Emergency Events Database
FAO	Food and Agricultural Organization
FEVD	Forecast Error Variance Decompositions
GDP	Gross Domestic Product
GES	Greedy Equivalence Search
GIEWS	Global Information and Early Warning System
GTD	Global Terrorism Database
ICA	Independent Component Analysis
IPCC	Intergovernmental Panel on Climate Change
IRF	Impulse Response Function
LiNGAM	Linear Non-Gaussian Acyclic Model
MA	Moving Average
OLS	Ordinary Least Square
PRIO	Peace Research Institute in Oslo

RATS	Regression Analysis of Time Series
RMSE	Root Mean Squared Error
SUR	Seemingly Unrelated Regressions
SVAR	Structure Vector Autoregression
UCDP	Uppsala Conflict Data Program
VAR	Vector Autoregression

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CHAPTER I

INTRODUCTION

The growing incidence of conflict and the search for ways to avoid it are one of the society's most challenging issues. Conflict destroys physical capital like infrastructure, disrupts human capital (e.g., via education achievements and health status), displaces people, and leads to health and poverty crises among other influences (Justino 2011). Note, however, that under certain circumstances, conflict can have positive effects. As Ruttan (2006) claims that conflict stimulated research and development (R&D), along with military and defense spending have played a primary and significant role in technology development. Nevertheless, in general, the more intense conflicts are, the more serious are the consequences they pose. For example, the typical cost of a civil war is estimated to be at least 50 billion dollars (Collier 2004).

In response to this substantial cost, many in the scientific community have explored what factors drive conflict as a way to give information to those trying to mitigate or prevent violent conflict as well as to promote or build peace. Diverse causes of conflict have been proposed, involving ones falling into social, economic and even climatological categories (Blattman and Miguel 2010). Specifically, some have been identified economic conditions (e.g., rate of economic growth), operation of state institutions, existence of ethnic nationalism, and level of secondary school attainment as drivers. For example, Collier (2004) states that the most vital drivers of conflict are economic elements. Furthermore, Collier (2004) points out that it is fairly easy for the poorest countries to be caught in the "conflict trap", a vicious cycle of economic decline and war. Therefore, they argue that international efforts are needed to assist those impoverished countries in avoiding the "conflict trap".

In addition, there exists a well-known argument that natural resources endowments and their governance are drivers. Classic economic theory suggests that sufficient natural resources can accelerate economic growth as "physical and human capital". Nevertheless, our world has witnessed many conflict events mainly happening in African countries, which are endowed with ample natural resources such as diamonds and oil with perhaps governance as the cause. Moreover, an increasing number of studies have found robust evidence supporting that nations with abundant resources tend to perform badly in growth (Sachs and Warner 2001). In other words, it is the "natural resource curse".

Climate change has also been mentioned as a potential contributing factor. Nevertheless, due to the inherent complexity of conflict, assertions on the importance of the potential causes mentioned above remain controversial and under investigation.

Many issues regarding the interrelationship among climate, conflict and economics remain unsolved. The broad objective of this dissertation is to econometrically investigate the extent to which climate and selected economic forces contribute to conflict or are influenced by conflict. Specifically, the following topics will be addressed.

- The climate-conflict nexus. I will empirically explore the association between climate and the global incidence of conflict cases.

- The extent in a case country setting to which conflict is influenced by or influences commodity prices and consumption. In particular, I will explore this utilizing data from the undivided Sudan, a country in Africa that has been going through conflict for a majority of its history. Specifically, two aspects will be examined.
    - The relationship between food prices and conflict outbreak. This will be achieved by studying the dynamic relationship of commodity prices and conflict onset.
    - The way commodity demand is influenced by or influences conflict in the form of terrorism.

The work done in this dissertation will be reported through three essays. Chapter II presents the results of efforts on climate and conflict globally. Chapter III reports on the analysis regarding prices and conflict in Sudan. Chapter IV reports on the analysis of relationships between demand and terrorism in Sudan.

CHAPTER II

CLIMATE AS A CAUSE OF CONFLICT: AN ECONOMETRIC ANALYSIS*

Introduction

Both climate change and conflict pose threats to the economy, human welfare, and security. A number of authors have argued that climate is one of the drivers of conflict but there have been counterarguments (e.g., Hsiang et al. 2013; Benjaminsen et al. 2012). Here we investigate the strength of that association using a global dataset. In particular, we econometrically examine if climate directly or indirectly influences the probability of conflict and estimate the effects of projected climate change on conflict incidence.

Numerous countries have suffered or are suffering from conflict in recent history, with devastating and long-lasting effects. Specifically, conflict has eroded physical assets like infrastructure and homes, reduced services from natural assets via destruction or confiscation for military purposes, worsened economic conditions through job losses and high inflation, weakened the labor force via injuries or deaths, and worsened social assets by forced migration or psychological damages (Verner 2010). The literature advances a set of diverse factors that can provoke conflict including social, political, natural resource, economic, foreign aid and climatic ones, but there still remains debate

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about the linkages and the strength of association among these items (Blattman and Miguel 2010).[1]

The past few decades have witnessed unprecedented climate change with an accelerating rising global average temperature, and observed regional changes in precipitation, extreme event frequency, and increasing sea level among other diverse effects (IPCC 2013, 2014). A continuing degree of future climate change has been projected by many scientific groups. Substantial evidence indicates such climate change influences environmental and social systems (e.g., IPCC 2007 a, b, and c, 2012, 2013, 2014; Carnesale and Chameides 2011; USCCSP 2008). In particular, a series of IPCC reports (2007 a, b, and c, 2012, 2013, 2014) document observed climate change consequences, including melting ice and snow, altered crop and livestock yields, declining populations of certain plants and animals, increased damages from pests, and exacerbated extreme event effects.

In recent years, there has been substantial speculation that climate conditions contribute to conflict (e.g., Burke et al. 2009; Hsiang et al. 2013). While it is unlikely that climate is the unique or dominant cause of conflict, it may act as an accelerant. For instance, climate change may give rise to resource scarcities like reduced availability of water and food, which could spur riots, and protests and in turn violent conflict. That's why climate change is termed "a threat multiplier" by military planners (CNA 2007). In fact, given that climate conditions can cause for example food shortages, pest and

[1] Blattman and Miguel (2010) state that the finding that economic conditions are correlated with conflicts is the most significant empirical conclusion in the current literature.

disease expansion, and water scarcity, it is not surprising that climate could trigger conflict. Recently, the Intergovernmental Panel on Climate Change (IPCC) examines evidence of the interconnection and calls for more research (IPCC 2014). We therefore examine the climate – conflict nexus as it arises in the global data hopefully improving the understanding of the interactions and shedding light on policy design and implementation. Our parametric and semiparametric analyses provide robust evidence suggesting that the probability of civil conflict outbreak could increase due to a decline in precipitation compared to last year.

Literature Review

IPCC (2014) devotes a chapter to "human security" and includes a section on "conflict". The Secretary General of the United Nations (Ki-Moon 2007) states that the conflict occurring in Darfur was being caused by "an ecological crisis, arising at least in part from climate change". Also the "Arab Spring" – wave of protests, uprisings and armed conflict that spread across the Arab world – has been argued to have underlying climatic causes (Werrell and Femia 2013). Admittedly, it is also widely acknowledged that brutal governments or wide gaps in income and many other non-climatic factors may induce conflict (CenSEI 2012).

Over the past decade, a rapidly growing body of literature has explored the connection between climate and conflict. Here, we generally discuss several of the commonly asserted causal chains. We also note that Dell et al. (2014) provides a thorough and exhaustive summary of the current climate-conflict related literature.

Many studies have focused on linkages between precipitation, temperature, and conflict. Burke et al. (2009) conclude that there is a robust linkage between temperature and civil war in Africa with warmer years sparking wars. Gartzke (2012) examines relationships between global average temperatures and interstate conflict, but finds that climate is not necessarily a causal influence. However others suggest that the reason for such results is ignoring non-stationarity of the dataset (Devitt and Tol 2012).

Miguel et al. (2004) investigate the interrelationship between civil war and rainfall variability in Africa (Theisen et al. 2013). They find that a decline in rainfall can fuel conflict. Hendrix and Glaser (2007) arrive at a similar conclusion in sub-Saharan Africa. However, Ciccone (2011) argues that a misspecification of rainfall could account for such a conclusion and that inclusion of rainfall level might be more appropriate. Miguel and Satyanath (2011) illustrate that rainfall variations are treated as instruments in their paper and that Ciccone's (2011) arguments lack theoretical support. Hendrix and Salehyan (2012) conclude that African extreme rainfall deviations – drought and heavy rainfall – are associated with greater likelihood of conflict. Maystadt and Ecker (2014) find that longer and more severe droughts contribute to conflict outbreak in Somalia. Hsiang et al. (2013) detects a significant correlation between climate and human conflict based on a meta-analysis of 60 previous studies.

Nel and Righarts (2008) suggest that natural disasters can significantly spur violent conflict particularly in low- and middle- income nations. In contrast, Slettebak (2012) asserts that climatic natural disasters lessen the outbreak of civil war by suppressing aggression. Besley and Persson (2011) find that natural disasters enhance the chance of civil war. Bergholt and Lujala (2012) obtain the opposite conclusion: finding climatic disasters do not affect conflict. Theisen et al. (2013) argue that the different results likely stem from an endogeneity problem. A number of other studies do not find any significant relationship (e.g., Buhaug 2010; Benjaminsen et al. 2012).

Raleigh and Urdal (2007) state that a higher level of water scarcity increases the risk of conflict. Lecoutere et al. (2010) reaches a similar conclusion as do Tir and Stinnett (2012). Dinar et al. (2007) offer a different viewpoint, indicating that nations usually prefer to cooperate with each other instead of fighting when facing water scarcity issues.

To date, it appears that research with a longer time horizon shows climate affects conflict as opposed to studies with a shorter time period. Additionally, climate probably indirectly affects conflict through multiple channels such as institutional effectiveness, human migration, crop failures and water shortage (Scheffran et al. 2012). Generally the literature aforementioned does not collectively permit drawing systematic conclusions about the climate-conflict relationship. IPCC (2014) has suggested that more extensive analysis is needed regarding the interconnection across different environmental conditions and conflict events over an extended time period. We therefore examine the climate-conflict nexus as it arises in global data in order to improve understanding of the interactions, and to support policy design and implementation to mitigate conflict and build the conditions for peace.

Objectives and Procedures

This study seeks to examine the linkage between climate and conflict using global data. This will be done by econometrically estimating a model that predicts the probabilities of conflict incidence and how they are affected by climate variations. The dataset unifies measures of historical annual climate, conflict incidence and country related characteristics. The final dataset ranges from 1950 to 2006, covering conflict events in 165 countries. The dataset is discussed in the following subsections.

Climate Data

Historical country-year level climate data were drawn from Dell et al. (2012)[2] who sourced data from the Terrestrial Air Temperature and Precipitation: 1900–2006 Gridded Monthly Time Series (0.5 × 0.5), Version 1.01 (Matsuura and Willmott 2007). Additionally, Dell et al. (2012) computed country-year level averages using a population-weighting scheme. Dell et al. (2012) provide a detailed description of the climate data and their processing.

Following Miguel et al. (2004), we also include data on "weather variations" from prior years.[3] In particular we construct a "temperature variation" variable as the

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[2] Other global databases could have been used, such as the Global Precipitation Climatology Project (GPCP) database, the National Centers for Environment Prediction (NCEP) database and the U.N. Food and Agricultural Organization Climatic (FAOCLIM) database. The major reason we used Dell et al. (2012) is the region to country wide weighting scheme. Despite the different mechanisms and standards among the three aforementioned global databases, they are highly correlated, which would probably produce similar results (Miguel et al. 2004).

[3] NASA indicates that the measure of time determines the difference between weather and climate: "Weather is what conditions of the atmosphere are over a short period of time, and climate is how the atmosphere 'behaves' over relatively long periods of time." Therefore, we hereafter use the "weather" instead of "climate" as Dell et al. (2012) do, given that we study the annual levels of temperature and precipitation in this paper.

proportional change from the previous year, $(T_{i,t} - T_{i,t-1})/T_{i,t-1}$, and denote it as ΔT_{it}, where $T_{i,t}$ is the temperature observation for country i in year t. Likewise, we compute a precipitation variation variable as $\Delta P_{it} = (P_{i,t} - P_{i,t-1})/P_{i,t-1}$, where $P_{i,t}$ is the precipitation observation for country i in year t.

Conflict Data

Data on conflict incidence are drawn from the UCDP/PRIO Armed Conflict Dataset, which defines armed conflict as "a contested incompatibility that concerns government and/or territory where the use of armed force between two parties, of which at least one is the government of a state, results in at least 25 battle-related deaths" (Gleditsch et al. 2002; Harbom and Wallensteen 2012)).[4] Taking into account the complexity of conflict, we narrow our research scope down to civil war. Specifically, we mainly focus on conflict incidence, which is coded as 1 for all country-year observations with at least one conflict and 0 otherwise.

Other Country Characteristics Data

It is well acknowledged that there exist many determinants of conflict. However, it is almost impossible to account for and precisely measure all of them. Consequently,

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[4] Compared with the widely used Correlates of War (COW) database, UCDP/PRIO dataset has more transparent structure and relatively lower threshold of conflict definition in terms of battle deaths (25 yearly battle-related deaths), thus incorporating more relatively small conflict events where these low intensity conflict events probably play a significant role in small countries (Bergholt and Lujala 2012; Miguel et al. 2004). Admittedly, the main disadvantage associated with the UCDP/PRIO dataset is the lack of accurate conflict information, such as the exact date and numbers of conflict deaths, setting limits on their use in empirical research (Miguel et al. 2004). Nonetheless, as we mentioned before, UCDP/PRIO dataset is still preferred given that it encompasses lower level conflict events than its peers do (Nel and Righarts 2008). Taking into account that conflict is fairly complicated and somewhat difficult to precisely define empirically, we decide to narrow our research scope down to civil war. Correspondingly, in the UCDP/PRIO database, civil war includes two categories: internal armed conflict, and internationalized internal armed conflict (Gleditsch et al. 2002; Harbom and Wallensteen 2012).

many kinds of forcing variables have been argued for inclusion along with alternative measurement methods. The control variables included in this study have been identified as significant components in fueling conflict by a majority of previous literature and are discussed below.

First, we include population size allowing that larger populations could impose a burden on local development and cause more potential conflict (Cervellati et al. 2011; Fearon and Laitin 2003). Goldstone (1991) and Salehyan and Hendrix (2014) argue that, societies, especially agrarian societies, with faster population growth rates are more likely to exhibit conflict than those with slower rates.

Second, we include economic development in the form of GDP per capita in terms of purchasing power parity (PPP) following Nel and Righarts (2008) and Hegre and Sambanis (2006). This allows for the possibility that lower economic levels may stimulate higher probabilities of conflict outbreak as argued by Hegre and Sambani (2006) and Salehyan and Hendrix (2014). Also per capita income reflects financial, military and police strength plus may reflect the ease of recruiting young men to become rebels (Fearon and Laitin 2003).

Third, an indicator of political regime type is incorporated. That indicator ranges from -10 (strongly autocratic) to 10 (strongly democratic) and accounts for the possibility that political status might affect conflict likelihood (Cervellati et al. 2011). These data are obtained from the Polity IV Project (Marshall and Jaggers 2012). Following Hegre (2001), a squared term is also added to allow for a curvilinear effect. That is, we permit countries with the least (-10) and most (10) democratic regime types to be less likely to experience conflict. Both population and GDP per capita data are obtained from the Penn World Table version 7.1 (Heston et al. 2012) and log-transformed to reduce skewness (i.e., to generate less bias at the extremes). In addition, all of the control variables are lagged one year, in order to take into account the probability of reversed causality and time lags (Theisen 2008).

To consider other country characteristics, such as ethnic polarization and geographical characteristics, we include country fixed effects that are designed to exclude these time invariant influences. Other country level control variables, like income inequality or unemployment rate, are not incorporated due to missing or dubious values among the available datasets (Miguel et al. 2004). In addition, we investigate models with and without time trend in accordance with the arguments in Nelson and Kang (1984).

Methodology

The analysis will be conducted in a rolling window scheme, which allows for a system that is evolving over time (Swanson 1998). That is, the length of the time period for the estimations is fixed but is treated in a way that permits out-of-sample reliability testing. Given that our whole dataset spans 57 years, the last ten years (1997 – 2006) are used for out-of-sample model validation. Particularly, we keep a fixed length of 47 years as the estimation window and then generate one-step-ahead forecasts (i.e., do a prediction for the 48th year). Initially we use the subsample 1950 - 1996 to predict conflict incidence in 1997, and then estimate using the subsample 1951 - 1997 to predict conflict incidence in 1998. We continue this procedure 10 times and at each time the fixed estimation window is rolled ahead one year. In turn, we evaluate predictive capability of the estimated models with two criteria, by comparing the 10-year out-of-sample probability forecasts with the true values. Finally, the best model is selected through a model-validation process.

Below we describe the construction and specification of models used in our analysis.

Parametric Models

Given that our data are collected over multiple time periods for individual countries, panel models are employed to take into account unobserved country level heterogeneity. This helps avoid biased estimations. Another obvious benefit is that panel datasets possess more data points, thus they increase degrees of freedom, flexibility and reduce the possibility of collinearity among covariates (see, e.g., Hsiao (2003)).

The general reduced-form panel model can be characterized by the following function (Dell et al. 2014):

$$y_{i,t}^{*} = \boldsymbol{\beta f}(\boldsymbol{C_{i,t}}, \boldsymbol{C_{i,t-1}}) + \boldsymbol{\gamma X_{i,t-1}} + \alpha_i + \theta_t + \epsilon_{it} \tag{2.1}$$

where i and t index country and year. $y_{i,t}^{*}$ is the outcome of interest – the conflict probability. $\boldsymbol{C_{i,t}}$ represents historical weather variables and a vector of general functional form $\boldsymbol{f}(\cdot)$ is included to permit flexible implications of climatic variables. $\boldsymbol{X_{i,t-1}}$ is a vector of control variables (covariates), containing GDP per capital, political regime types and population. α_i captures the country-specific and time-invariant characteristics, commonly known as “fixed effects”. θ_t is a time trend, which enables us to identify the relationships from idiosyncratic disturbances by neutralizing possible common trends

(Dell et al. 2014). ϵ_{it} is an idiosyncratic error term with $E(\epsilon_{it}) = 0$, and those disturbances can be correlated across time horizon for each country. $\boldsymbol{\beta}$ is a vector of parameters to be estimated that give weather effects on conflict; $\boldsymbol{\gamma}$ is also a vector of parameters that measures the impacts of the other country-related characteristics on conflict.

Before proceeding, several caveats are worth mentioning. First of all, many studies (e.g., Miguel et al. 2004) utilize climatic variables as instruments to study other non-climatic phenomenon, at the cost of imposing exclusion restrictions to obtain causal inference. Weather instruments, however, may not be strong enough when dealing with the worldwide dataset. Hence the results of subsamples are usually weather dependent (Burke 2012). The reduced-form panel method utilized in this study can achieve more robust results, due to relatively fewer assumptions of identification as argued in Dell et al. (2014). Secondly, we incorporate fixed effects to account for unobserved country level determinants that may influence the likelihood of conflict. Additionally, as Burke (2012) points out, the standard errors need to be robust during estimation to account for heteroscedasticity, and estimation should be performed by clustering across countries to avoid potential serial correlation.

Since the dependent variable $y_{i,t}$ is binary, we use a panel logit approach to estimate the probability of conflict (Greene 2003; Hsiao 2003; Burke and Leiga 2010). The model takes the form

$$Pr\left(y_{i,t} = 1 \middle| \boldsymbol{C_{i,t}}, \boldsymbol{C_{i,t-1}}, \boldsymbol{X_{i,t-1}}, \alpha_i, \theta_t\right) = G(\boldsymbol{\beta f}(\boldsymbol{C_{i,t}}, \boldsymbol{C_{i,t-1}}) + \boldsymbol{\gamma X_{i,t-1}} + \alpha_i + \theta_t) \quad (2.2)$$

where $G(\cdot)$ is the logistic distribution. For estimation, a conditional maximum likelihood method is employed.[5] We choose the logit models instead of the probit, since it has been argued that probit models are not suitable under fixed effects treatments (Burke and Leiga 2010; Greene 2003).

Semiparametric Models

It is well acknowledged that due to the strict assumptions about functional forms, parametric panel models can be misspecified and give rise to inconsistent estimators as a result. To circumvent this problem, we also consider semiparametric single index models. They generally serve as a compromise between confining parametric models and flexible but difficult to estimate fully nonparametric models (Hristache et al. 2001). Additionally, such models are readily interpretable and maintain much of the flexibility of nonparametric models (Härdle et al. 2004). For details about the single index models, please refer to Ichimura (1993) and Li and Racine (2007).

Following Li and Racine (2007), the single index model is expressed as

$$Y = g(\boldsymbol{X}'\boldsymbol{\beta_0}) + u \tag{2.3}$$

where the dependent variable Y is the civil conflict measurement, the vector of independent variables $\boldsymbol{X}$ $(q \times 1)$ represents the set of weather and country characteristic variables, $\boldsymbol{\beta_0}$ $(q \times 1)$ stands for a vector of parameters to be estimated, and u is the disturbance term with $E(u|\boldsymbol{X}) = 0$. Aside from weather measures, the explanatory variable $\boldsymbol{X}$ includes economic factors, population and democracy degree. $\boldsymbol{X}'\boldsymbol{\beta_0}$ is termed

[5] Unconditional maximum likelihood (UML) yields biased estimated coefficients for logit models (Hsiao 2003).

as a “single index” because it is a scalar. Only the linear index ($\boldsymbol{X'\beta_0}$) is specified whereas the functional form $g(\cdot)$ remains unknown. To some extent, a single index model can be treated as a generalized logit model, since it keeps the linear index unchanged and relaxes the requirement of function $g(\cdot)$ to be arbitrarily smooth (Härdle et al. 2004).

Many estimation approaches have been proposed for this model. The two most widely used methods are those introduced by Ichimura (1993) and Klein and Spady (1993). The former is appropriate for continuous outcomes while the latter is best suited for binary values (Racine 2009). Given the context of binary variable (conflict incidence), we use the kernel-based estimator by Klein and Spady, with bandwidth is determined by the method of cross-validation.

Model Selection Criteria

We utilize two commonly-used criteria to assess the predictive performance of models aforementioned.

The first measure is the Brier score, a quadratic scoring rule with a rich history of applications (Brier 1950; Bessler and Ruffley 2004). The Brier score evaluates the prediction ability of models with binary or continuous dependent variables and offers an overall picture of their performance. The lower the Brier score, the better the predictive performance. Yates (1988) further provides a covariance decomposition of the Brier score for more thorough and extensive analyses, which allows accounting for both calibration and resolution by different components.[6] In particular, one term called "calibration-in-the-large" (or Bias) captures the models' general miscalibration over all the probability forecasts. On the other hand, the covariance of predictions and actual outcomes index represents models' resolution or sorting ability. That is, it reflects the ability of a model to distinguish occasions in which event does occur from those where it does not, which is regarded as the heart or core of forecasting strength (Yates 1982). Here higher covariance means better responsiveness of the predictions to the available information. More discussion about each component of Brier score will be presented below, together with the model comparison.

Another way to visualize and evaluate models' performance involves use of the receiver operating characteristic (ROC) curve (Fawcett 2004). The ROC curve characterizes the true positive rate ("sensitivity") versus the false positive rate (1- "specificity") for all possible cutoffs (Fawcett 2004). On the grounds that ROC curves capture models' discrimination performance in a two-dimensional way, it is probably easier to compare different models just based on one dimension – a scalar. Generally, this dimension reduction can be achieved by evaluating the area under the ROC curve, abbreviated AUC (Fawcett 2006). An area of 0.5 means a useless model, which is equivalent to random guessing, such as flipping a coin (tail or head); an area of 1 indicates a perfect model, which can unerringly tell when conflict events do and do not

[6] Calibration refers to a model's ability to issue a probability that is consistent with its relative frequency, ex post; Resolution refers to a model's ability to partition uncertain outcomes into subgroups that vary from its relative frequency in the long-run (Bessler and Ruffley 2004).

occur. That is, the higher the AUC, the better the discrimination ability of the model. Generally an AUC above 0.8 is considered to be “good” (El Khouli et al. 2009).

Empirical Results

As Friedman (1953) asserts, “The ultimate goal of a positive science is the development of a ‘theory’ or ‘hypothesis’ that yields valid and meaningful (i.e., not truistic) predictions about phenomena not yet observed.” Accordingly, in this study, we focus on out-of-sample predictive ability to choose the best model.

As aforementioned, a rolling window approach with a fixed time length is implemented to generate dynamic one-step-ahead forecasts of conflict incidence for 1997 – 2006. Additionally, given controversy regarding the inclusion of time trend we consider models with and without the trend variable. We will also look at models with and without adjustments for stationarity. The results in four models are listed as below.

Model 1: Original Series + Quadratic Time Trend

Model 2: Original Series + No Time Trend

Model 3: Stationary Series + Quadratic Time Trend

Model 4: Stationary Series + No Time Trend

In our dataset, GDP is the only nonstationary series (I (1)), thus we take the first difference to render it stationary.

Model Evaluation

In what follows, we will assess models’ predictive performance through several widely used criteria.

Brier Score and its Yates' Covariance Decompositions

The Brier scores for one-step-ahead forecasts are presented in Table 1. Components from the Yates' covariance decompositions are displayed below them.[7]

Table 1. Brier Scores and Their Yates' Decompositions

	Panel Logit Model			
	(1)	(2)	(3)	(4)
Brier Score	0.1456	0.1385	0.1452	0.1386
$Bias^2$	0.0138	0.0072	0.0140	0.0081
Scatter	0.0013	0.0017	0.0011	0.0016
MinVar	0.0000	0.0000	0.0000	0.0000
Dvar	0.1298	0.1298	0.1298	0.1298
2Cov	-0.0006	0.0003	-0.0003	0.0010
	Single Index Model			
	(1)	(2)	(3)	(4)
Brier Score	0.1170	0.1131	0.0948	0.0863
$Bias^2$	0.0001	0.0004	0.0000	0.0000
Scatter	0.0213	0.0214	0.0383	0.0338
MinVar	0.0026	0.0034	0.0150	0.0172
Dvar	0.1299	0.1299	0.1298	0.1298
2Cov	0.0369	0.0421	0.0884	0.0946

Notes: Yates' decompositions of Brier Score is given by the numbers below "Brier score" in each column. Brier Score=DVAR+MinVar+Scatter+ $Bias^2$-2Cov.

On the basis of Brier score, the semiparametric models exhibit better predictive power than the corresponding parametric models. Generally, within either parametric or semiparametric models, models without time trend perform better than models with time

[7] Note that in the case of a binary dependent variable, the Mean Squared Error (MSE) is equivalent to the Brier score. That is, the increase in the Brier scores reflects deterioration in models' forecasting ability.

trend (Model 1 vs Model 2; Model 3 vs Model 4). Models with stationary series do a better job than models with original series (Model 1 vs Model 3; Model 2 vs Model 4). The only exception is that Model 2 and Model 4 for parametric models perform about the same. Additionally, one natural question that arises is: in what way do the semiparametric models outperform the parametric ones? This can be answered by examining the results from the Yates' decomposition.

Generally the semiparametric models show a lower "Bias^2"[8] (0.000 – 0.004), they therefore do a better job of matching the mean forecasts to the relative frequency of conflict. The semiparametric models are more sensitive to the information related to the outcomes in the future as measured by the covariance between forecasts and the outcome index (labeled as "2Cov"). Moreover, the positive sign of that term indicates the responsiveness is in the right direction.[9] Nevertheless, the semiparametric models do not always outperform the parametric models. For instance, they have larger scatter values (labeled as "Scatter"), which quantify the overall noise in the forecasts. Similarly, semiparametric models portray a larger minimum forecast variance (labeled as "MinVar"), which reflects the minimum amount of forecast variability that must be tolerated (Yates 1988).

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[8] "Dvar" is the variance of the outcome index and will not be discussed here, since it is out of the models' control (Bessler and Ruffey 2004); "MinVar" is the minimum forecast variance; "Scatter" could be regarded as the excess variability of the forecast (Casillas-Olvera and Bessler 2006); "Bias2" is the squared term of "Bias", where "Bias" is the "calibration-in-the-large"; "Cov" is the covariance between forecast and actual outcomes.

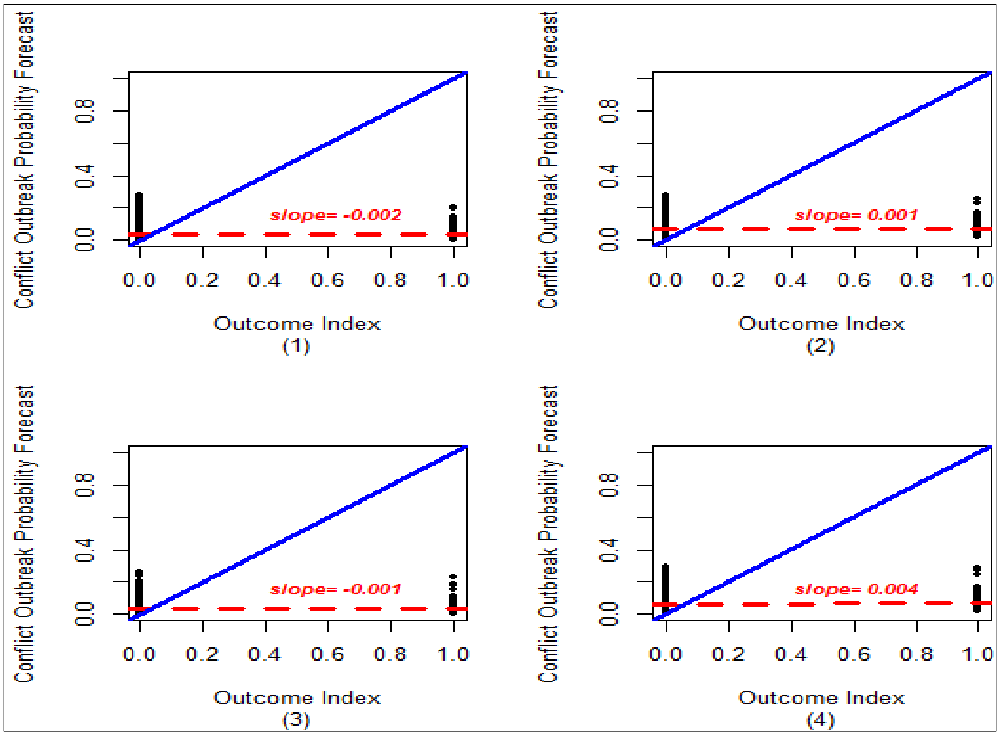
[9] In some cases with negative covariance term (e.g., parametric Model 1 and 3), zero covariance might be chosen instead to minimize the Brier score (Casillas-Olvera and Bessler 2006).

To summarize, compared to the semiparametric models, parametric models are superior with respect to the characteristics of "Scatter" and "MinVar", whereas they are inferior with regarding to the metrics of "$Bias^2$" and "2Cov". Intuitively, covariance reflects the responsiveness of the model to the information pertinent to the conflict incidence, while the scatter indicates the responsiveness of the model to the information not pertinent to the conflict incidence (Casillas-Olvera and Bessler 2006). In this way, we propose that parametric models are better at filtering irrelevant information or excluding noise. However, they screen out some vital information as well, which may play a key role in predicting the probability of conflict incidence. On the other hand, semiparametric models perform comparatively better in capturing useful information. Nevertheless, it is highly likely that they achieve higher covariance values at the cost of incorporating irrelevant knowledge. To some extent, our results appear to be consistent with the results cited in Yates (1982)[10] and Bessler and Ruffley (2004), where an increase in scatter and covariance occurred together. A caveat has to be made here. The component called variance of the outcome index (labeled as "Dvar") has not been discussed in preceding sections. The major reason is that it is entirely out of the models' control, representing the base rate in which conflict does take place (Bessler and Ruffley 2004). All in all, based on the Brier score and its covariance decomposition, the semiparametric model with stationary series and without time trend (i.e., Model 4) outperforms the other alternative models considered.

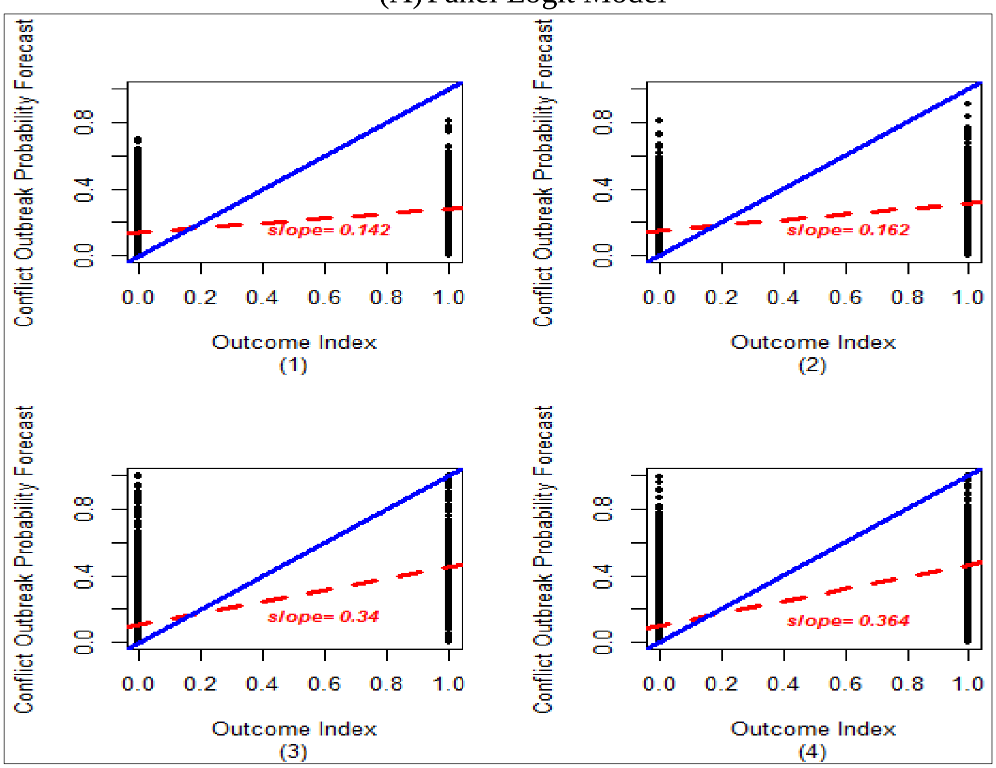
[10] Yates (1982) finds that the subject with the best Brier score has both higher scatter and covariance, compared to the subject with the medium Brier score.

Beyond the numeric analyses above, we also present covariance graphs on the model performance (Figure 1). They reflect the resolution ability among models, distinguishing conflicts that take place from those that do not take place. On the x-axis, 0 means conflicts that happen while 1 implies conflicts that do not happen. Accordingly, y-axis represents the probability forecasts for the two kinds of outcomes (i.e., 0 and 1). Therefore, we seek to obtain the desired model that generates low probabilities (at or near 0) for the outcome with 0, and high probabilities (at or near 1) for the outcome with 1 (Casillas-Olvera and Bessler 2006). In other words, models with perfect resolution (or sorting) ability correspond with the 45° line (i.e., the solid line in each sub-graph in Figure 1). The dashed-line is the covariance graph for each model by regressing the probability forecasts on the dummy outcome index.

Comparison of graphs in panel (A) and (B) indicates the superiority of semiparametric models relative to parametric models in sorting. Parametric models assign low forecast probabilities to both outcome index 0 and 1, so the dashed lines in panel (A) are much flatter than those of semiparametric models in panel (B). Admittedly, semiparametric models' covariance graphs show a larger dispersion in their forecasts for outcome index 0 and 1 than parametric ones. Still, their larger slopes (0.142 – 0.364) compared to the parametric ones' (-0.002 – 0.004) strongly indicate their better goodness of sorting conflict incidence cases, under the context of conflict. Particularly, the semiparametric model 4, again, dominates, owning to its largest slope (0.364) among all the models investigated here.



(A) Panel Logit Model



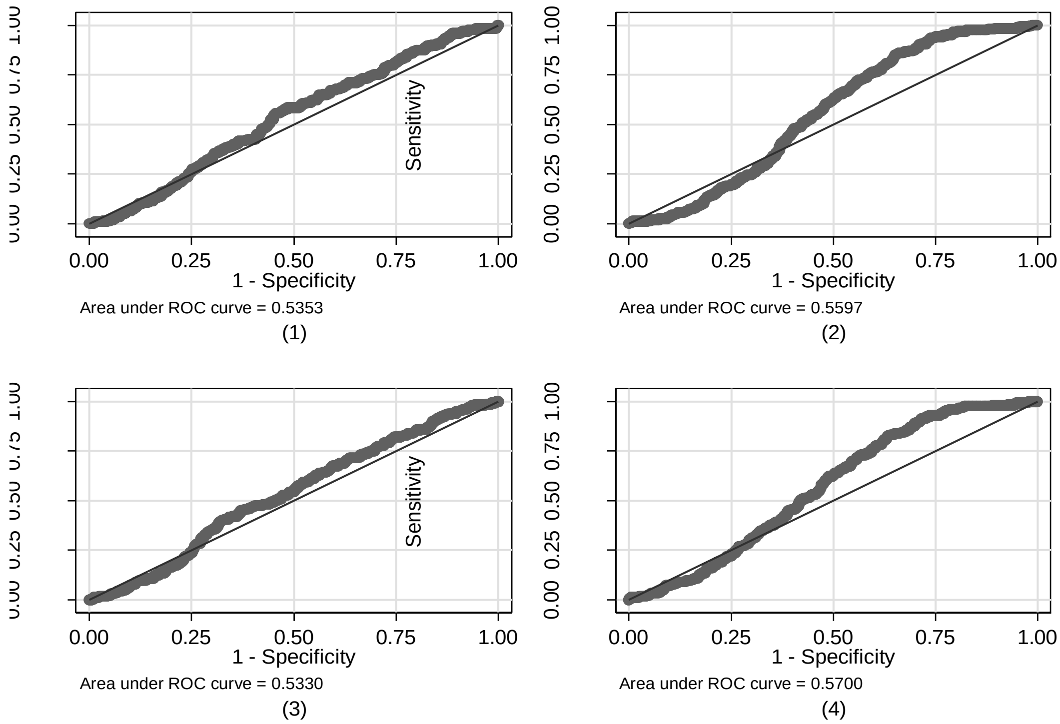
(B) Single Index Model

Figure 1. Covariance Graph for Probability Forecasts on Conflict Incidence

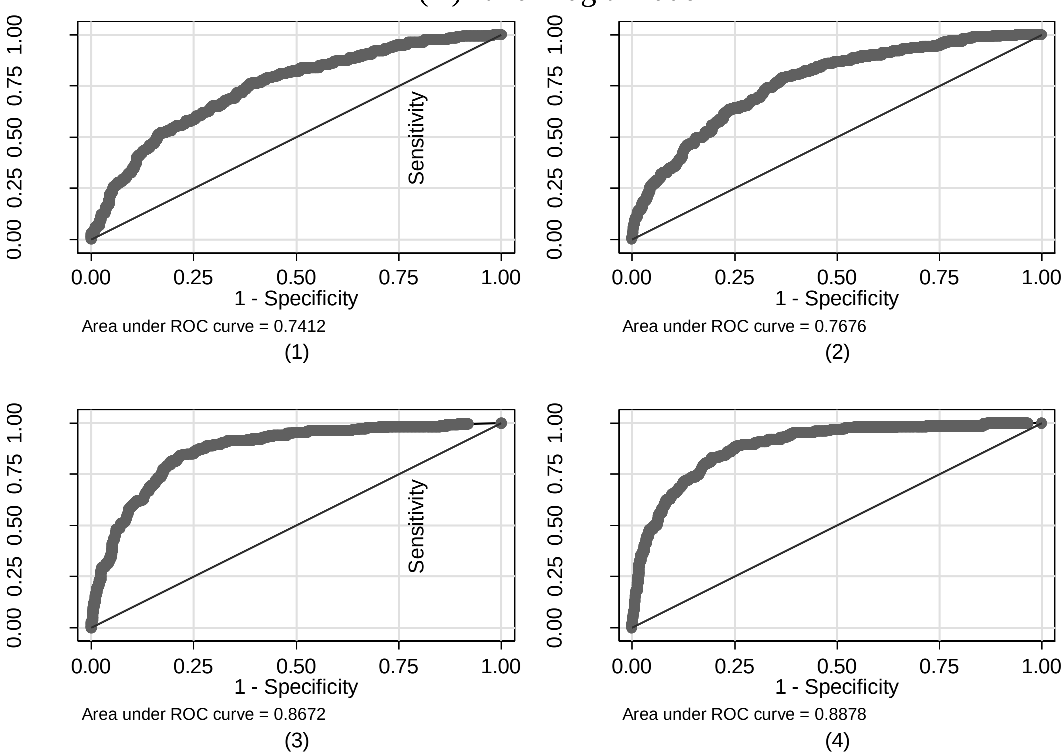
Receiver Operating Characteristic (ROC) Curve

ROC curves for all models studied are displayed in Figure 2. The diagonal straight line y=x stands for models containing no useful information, while the point (0, 1) symbolizes the perfect classification. In other words, the better models lie in the upper triangular region and are further away from the diagonal.

As we mentioned earlier, we will use the area under the ROC curve (AUC), a single scalar, to compare model classification abilities. It can be seen that all parametric models have the AUC of 0.5353 – 0.5700, while all semiparametric models have the AUC of 0.7412 – 0.8878. Moreover, all of these values are statistically significant greater than 0.5 using the Wilcoxon nonparametric tests. That is, all models do better in prediction, compared to random guessing. Interestingly, the results agree with those suggested by the Brier score: namely models without time trend outperform models with time trend; semiparametric models outperform parametric ones. Consequently, depending on the values of AUC, the semiparametric model with stationary series and without time trend (Model 4) is the best candidate model (AUC = 0.8878).



(A) Panel Logit Model



(B) Single Index Model

Figure 2. Receiver Operating Characteristic (ROC) Curve

Weather Effects Results

Now we use the best performing single index model (stationary series, without time trend – Model 4) to analyze the climate conflict nexus with the whole dataset.

To quantify the effects of the weather variation on conflict incidence, we compute the Average Marginal Effects (AME). These measure the change in probability of conflict outbreak when an independent variable (i.e., weather variation) increases by one unit while keeping all the other independent variables unchanged. To make the results comparable across different studies, the effects are standardized by transforming the original AME to a relative change in the dependent variable – conflict incidence (Hsiang et al. 2013). Given that only the coefficient of precipitation variation (not temperature variation) is statistically significant during the estimation, we focus on the standardized AME of precipitation variation in this discussion

The panel logit model suggests that a 1% increase in the difference in precipitation from this year to last lowers the probability of civil conflict outbreak by 5.68% at the 0.01 level of significance (Std. Err = 0.0033). Likewise, the single index model also implies a 3.37% in conflict probability decrease with a 1% higher amount that this year's precipitation than last year's. As a consequence, the optimal out-of-sample forecasting model, selected through a rolling window scheme, suggests that a higher level of precipitation this year relative to last will statistically significantly lower the risk of civil conflict.

Additionally, we find some interesting results when estimating the panel logit model, which is displayed in Table 2.[11]

Table 2. Dependent Variable: Conflict Incidence, 1950 – 2006

Independent Variable	Panel Logit Model
Variation in Temperature at t	-0.003
	(0.847)
Variation in Precipitation at t	-0.225**
	(0.101)
First Differenced Log(GDP) at t	-3.819***
	(0.935)
Regime Type at t-1	-0.010
	(0.033)
Regime Type Square at t-1	-0.011*
	(0.006)
Log(Population) at t-1	1.640***
	(0.483)
Observations	3826
Pseudo_R^2	0.071
BIC	2565.4

standard error in parentheses

* p<0.1, ** p<0.05, *** p<0.001

[11] In semiparametric estimation, we set the first component of the coefficient vector equal to one to obtain scale normalization. The coefficients therefore are not interpretable, but we calculate the average marginal effects (AME) instead, to quantify the impacts of weather variation on conflict incidence.

Table 2 shows that the effect of precipitation variation on conflict incidence is significantly negative at the level of 0.05. Intuitively, the less the precipitation this year relative to the last the higher the probability of civil conflict the country may suffer from.[12] Such a robust result offers strong evidence of a negative relationship between precipitation abundance and civil war incidence, which is in line with the findings of several other studies (Miguel et al. 2004; Hendrix and Glaser 2007).

We do not find significant direct correlations between temperature variation and civil conflict, albeit the fact that many researchers advocate higher temperature increases the risk of conflict (Hsiang et al. 2013; Burke et al. 2009). Additionally, interesting findings emerge by looking at other country characteristics. For example, GDP growth has statistically significant negative impacts on conflict incidence while population shows significant positive effects. That is to say, a country with higher GDP growth and less population is less likely to experience civil conflict. In addition, the significant coefficient of the squared term of regime type indicates its curvilinear effects on conflict incidence, consistent with regimens at either end of the spectrum having less conflict.

Discussion

Both parametric and nonparametric estimates yield strong evidence that a lower level of precipitation this year relative to last increases the risk of civil conflict. This finding indicates that negative precipitation shocks could be drivers of conflict. Climate change can contribute to this. The Intergovernmental Panel on Climate Change (IPCC

[12] This conclusion also holds across all the models on sub-samples investigated here. The estimated coefficient on precipitation variation remains statistically significant and negative no matter what rolling window is applied.

2007a, 2013) predicts that total global precipitation will increase as a whole, whereas the patterns differ significantly across regions. In addition, variability of rainfall is projected to increase with 90% certainty, which may give rise to or intensify extreme events such as droughts or flooding. As a consequence, the predictions of increased variability and extreme event incidence portend greater conflict incidence. Analytically, suppose precipitation follows the normal distribution, with mean μ and standard distribution σ. An increase in variability means that the standard distribution σ becomes larger. In other words, precipitation data spreads out covering a wider range of values. The probability of extreme values (i.e., extreme low precipitation/drought or high precipitation/flood) therefore grows. This has implications for policy design regarding climate change and conflict.

Admittedly, apart from the potential drivers of conflict considered in this study, there also exist numerous other determinants that make countries (or areas) more susceptible to conflict. For instance, economic elements that reflect the development level of a nation are closely linked to the risk of conflict. Poverty, economic inequality, economic structures such as the primary commodities countries rely on, policies, and the like are all examples. Given myriads of potential conflict-inducing factors, we cannot conclude that precipitation variation contributes the most to the conflict outbreak. Nevertheless, we obtain some major findings as follows.

First of all, our analysis strongly suggests that efforts in conflict prevention and resilience building can be enhanced by several means. Certainly there is the obvious climate change mitigation or adaptation. Additionally, actions such as provision of irrigation or other water supply enhancements would lessen the impact of precipitation fluctuations in conflict prone areas at risk of water shortage. Furthermore, forecasts of places where climate change would increase the probability of adverse precipitation events can help target efforts on pre-conflict peacebuilding interventions, through means such as enhancement of adverse event early warning systems, enhanced water supply reliability, and drought resistance increases through agricultural research (e.g., drought resistant varieties and crops). Moreover, we feel the quantitative analysis may well benefit policy-makers and other stakeholders by predicting conflict hot spots in advance allowing potential preemptive actions. Second, methodologically we find semiparametric models are superior forecasters and this indicates such methods might be used in other conflict and climate related analyses.

Overall, this study has several attributes that advance the current literature. First we believe the semiparametric methods – single index models – provide an important method for analysis. In particular following Hristache et al. (2001) and Härdle et al. (2004), single index models could increase the flexibility compared with parametric models and avoid the "curse of dimensionality", which is a common issue among fully nonparametric models. Second, this study emphasizes models' predictive performance, in an effort to improve the predictive power and possible policy use of the resultant model. Lastly but not least, a rolling window approach, which requires repeated regressions over a sequence of rolling window with a fixed length, is adopted to achieve robust forecasts for model selection. It provides higher flexibility of potential structural changes and thus more sophisticated usage than other models rested on once-off breaks (O'Reilly and Whelan 2005).

There are some limitations of our research worth noting. First, there exist numerous other determinants that make countries (or areas) more susceptible to conflict. For instance, economic elements that reflect the development level of a nation are closely linked to the risk of conflict. Poverty, economic inequality, economic structures such as the primary commodities countries rely on, policies, and the like are all examples. Given myriads of potential conflict-inducing factors, we cannot conclude that precipitation variation contributes the most to the conflict outbreak. Second, because we use reduced-form methods, our research cannot fully reveal or distinguish the climate-conflict mechanisms underlying the relationship. Consequently, extensions are essential to further illuminate the precise causal pathway, allowing one to tailor more efficient and effective localized policies as discussed in Miguel et al. (2004) and Burke et al. (2014). Third, our estimation results reveal short-run linkages and additional work might be done on long-run impacts considering possible adaptation (Dell et al. 2014).

CHAPTER III

A CAUSAL EXPLORATION OF CONFLICT EVENTS AND COMMODITY PRICES OF SUDAN*

Introduction

Higher food prices have detrimental consequences on the socio-political events in developing countries (FAO–SIFSIA 2012) and have been shown to be related to civilian unrest as well (Bellemare 2011; Besley and Persson 2008; Goldstone 1982; Lagi et al. 2011; Smith 2014). World food prices surged to a record high in February 2011, which served as a catalyst for a series of protests in North Africa and the Middle East, including the 2011 "Arab Spring" (Bellemare 2011; Brinkman and Hendrix 2011). Although recent literature establishes causal linkages between food prices and conflict, the direction of the causality is still unclear. Provided that food prices continue to stay high, its causal direction and shock responses of conflict remain a germane investigation. Our study contributes to this strand of studies by investigating the causal relationships of staple commodity prices and conflict events in Sudan. Using Structural Vector Autoregression (SVAR) techniques and modern innovations of computer science search algorithms, we discover that commodity prices, especially imported ones, drive conflict events in Sudan.

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Consistent with the general experience in the developing world, the prices of staple foods in Sudan increased alarmingly in 2008 (FAO–SIFSIA 2012). The region has been beleaguered by intense armed conflict in recent years. Particularly, Sudan's second civil war (1983 – 2005) is characterized as one of longest enduring, catastrophic wars during the late 20th century (Say et al. 2012). On July 9, after the referendum in January 2011, South Sudan seceded from Sudan and became an independent country, indicating the end of Comprehensive Peace Agreement (CPA) which was signed in 2005 (FAO/WFP 2014). Despite the independence and enduring efforts at stabilization, Sudan remains volatile due to the frequency of low-medium level conflict onsets (Raleigh et al. 2010). Recent literature shows numerous factors driving conflict: growing population (Collier and Hoeffler 2004), natural resource endowments (Collier and Hoeffler 1998), economic conditions such as income levels and economic growth (Berazneva and Lee 2013; Blattman and Miguel 2010; Miguel et al. 2004), fragile institutions and geographical attributes (Blattman and Miguel 2010), quick and significant demographic changes such as migration (Goldstone 2002). However, a time variant examination of the topic is yet to be conducted. With the existing inequality and unrest across regions, the soaring food prices could exacerbate the weak purchasing power of its citizens (IFAD 2009). Given the conflict onsets, rising food prices and low political stability in the region, Sudan is an ideal country to investigate the dynamic relationships between cereal prices and conflict.

Sorghum, millet, and wheat are the main cereals consumed in Sudan (Hamid 2003). Sorghum is the highest consumed commodity followed by wheat and millet.

Sudan is self-sustainable in sorghum and millet production (Abdelrahman 1998), while it at most produces 20% of its net wheat demand (FAO/WFP 2011). Consumption of these cereals differs by regions and socio-economic status of the citizens. Sorghum serves as the main staple for the most impoverished in central and eastern Sudan, while millet is the staple for most people in Darfur and some regions in the western Sudan (FEWS NET 2014a). In current times, wheat is usually treated as a substitute for sorghum and millet in northern Sudan, especially in the urban areas (Mustafa et al. 2013; FEWS NET 2014a). Mustafa et al. (2013) report that the average consumption of wheat has increased to 1770.8 thousand tons in the 2000s from 743.5 thousand tons in the 1980s. Consequently, imports of wheat have increased substantially since 1999, and the imports amount accounted for about 75 percent of the wheat consumption from 2000 to 2010 (Mustafa et al. 2013). Increased imports caused higher price volatility and government intervention. Furthermore, the high volume of wheat imports absorbs almost all of the foreign exchange generated from total agricultural exports (Auad et al. 2007).

In a recent report, Famine Warning Systems Network (FEWS NET 2014b) reports that 3.3 million people would face stressed and crisis levels of food insecurity, mainly caused by increasing food prices and conflict. Mahran (1996) approaches this topic from demand and supply perspective. Misselhorn (2005), using meta-analysis based on 49 household economy local-level studies, reveals the causes of food insecurity in southern Africa including conflict, poverty, and environmental factors. Hadley et al. (2012) conduct twenty semi-structured interviews in Africa and conclude that the rise in food prices could decrease food security, including non-nutritional results. Given previous studies and reports, it is plausible to draw the conjecture that rising cereal prices, violent activities, and the food shortage in Sudan are not unrelated. However, contemporary research does not draw direct time variant inference between food prices and conflict, especially in the Sudanese context. We address this gap in the literature by studying a time series dataset on commodity prices and conflict events in Sudan. In this article, we attempt to use Inductive Causation (IC) methods (Spirtes et al. 2000) to inform us on contemporaneous structure. Our treatment of the non-Gaussian commodity treatment is different from the contemporary social science literature, as we employ Linear Non-Gaussian Acyclic Model. We use a Bernanke-like Structure Vector Autoregression (SVAR) model to summarize the dynamic causal relationships between commodity prices and conflict. The rest of the paper is organized as follows: Chapter III.2 provides a literature review on the relationship of food prices and conflict; Chapter III.3 introduces the major methodology applied; Chapter III.4 describes the dataset; Chapter III.5 presents the results of estimation and Chapter III.6 summarizes the conclusion and provides some policy implications.

Background and Literature Review

Current literature offers ample evidence of linkages between increasing food prices and conflict. While rising food prices may not be the direct drivers for conflict, they may well be latent drivers of conflict. High food prices increase food insecurity and can lead to social and political instability and conflict. A reverse causal flow can be argued as well. The outbreak of conflict may increase food prices because of radical ramifications such as increasing disease, death and displacement, soaring military expense, and capital damages (Brinkman and Hendrix 2011). The following offers further theoretical and empirical evidence of both directions.

Food Prices (Market) Affecting Conflict

The impoverished suffer the most from high food prices. For instance, in Africa, the under privileged spend almost half of their income on food (Smith 2013). Goldstone (1982) suggests that food protests often erupt with high unemployment and increases in food prices. Walton and Seddon (2008) find that food riots surged in the 1970s, due to the integrated world economy where local food prices were more influenced by global political economy (Bellemare 2011). Besley and Persson (2008) study civil war and conclude that higher world market export and import prices increase the probability of civil unrest. Similarly, Lagi et al. (2011) suggest that global food price peaks, beyond a certain threshold, could trigger social unrest with other possible contributing factors. Taking into account other determinants including government interventions, other pertinent research suggest that higher commodity prices are correlated with conflict in developing countries (Brinkman and Hendrix 2011). Recently, Smith (2014) utilizes an instrumental variable approach and concludes that in urban Africa a sudden surge of domestic food prices contributes to civil unrest. Nevertheless, some scholars argue the same causal direction with different effects. Demuynck and Schollaert (2008) demonstrate that a fall of tropical agricultural commodities' prices could fuel conflict by instigating a rebellion. Similarly, Brückner and Ciccone (2010) show that a drop in commodity prices increases the probability of civil war.

Conflict Affecting Food Prices

Conflict events tend to impede food production, input supplies, and output storage (Hitzhusen and Jeanty 2006). Consequently, slight changes in supply could greatly affect prices since the demand for food is essentially inelastic. Therefore, conflict and its associated political and social instability could drive food prices (Brinkman and Hendrix 2011). Sufficient evidence indicates that socio-political events and wars, especially armed conflict and terrorism, usually have significant effects on markets (Kollias et al. 2011). Guidolin and La (2010) study a large sample of internal and inter-state conflict events and conclude that national stock markets tend to perform positively when there is an onset of conflict rather than responding negatively.

To summarize, not only can high food prices lead to conflict, but also conflict could contribute to high food prices. For instance, riots swept through the Middle East and North Africa, partly resulting from high food prices. In turn, the insecurity afterwards disrupted the commodity markets (Brinkman and Hendrix 2011). The vicious cycle can cause even higher food prices and more intense conflict events.

Methodology

As our data on commodity prices and the number of conflict events are observed in time sequence. Recent explorations of such time variant data on commodity prices include time series analysis of food and energy prices in India by Bhatt and Kishor (2015) and US food prices by Lambert and Miljkovic (2010). We augment their approach by considering a structural representation and employing a non-Gaussian graphical network based algorithm to identify contemporaneous causation. We study the co-movement of commodity prices and conflict events through time with the vector autoregression (VAR) model. We follow Hsiao (1979) and construct a subset vector autoregression model to capture the relationship between the current position of commodity prices and conflict events combined with their lagged values, allowing for asymmetric lag length structure. In addition, new information in each period (innovations) is then modeled using methods from machine learning as first suggested in Swanson and Granger (1997), giving us a structural representation of commodity prices and conflict events in contemporaneous time (a structural VAR).

Vector Autoregression Model

Empirical Strategy

The unrestricted Vector Autoregression (VAR) (Sims 1980) allows every variable to affect every other variable in a system of equations with lags of the same length, whereas the subset VAR permits a differential lag structure among variables of the system. For example, variable y_{1t} may affect variable y_{2t} with one lag, whereas it may affect variable y_{3t} with three lags. Justification for permitting such differences relates to both estimation efficiency and forecasting accuracy (Briiggemann and Liitkepohl 2001). Sims (1980) labels the unrestricted VAR as a profligately parameterized model. The subset VAR can be treated as the traditional VAR, subject to zero restrictions (determined from data) on certain coefficients of lagged variables $(y_{t-1}, y_{t-2}, \dots, y_{t-p})$. Hsiao (1979) offers a procedure for placement of these zero restrictions (reviewed below).

Following Moneta et al. (2013), the basic structural VAR in matrix form is given as:

$$y_t = B_0 y_t + B_1 y_{t-1} + \cdots + B_p y_{t-p} + B x_t + \varepsilon_t \tag{3.1}$$

where y_t $(k \times 1)$ is a vector of k endogenous variables observed at time t. In this paper, y_t represents wheat price, sorghum price, millet price and number of conflict events $(k = 4)$. The variable x_t $(d \times 1)$ is a vector of exogenous variables at time t. We use a set of eleven monthly binary variables to capture seasonal effects. The matrices B_i $(i = 1, \ldots, p)$ are coefficients to be estimated, each associated with a particular lag of the left hand side endogenous variable y_t. The index p refers to the maximum number of lags generating our system (as we are considering the subset VAR, p lags may not be the same for all elements of the vector y_t). The matrix B_0 represents contemporaneous coefficient matrix, with a zero for each element of the main diagonal. The vector ε_t is a $(k \times 1)$ series of white noise innovations, where $E(\varepsilon_t \varepsilon_s') = \Sigma,$ if $t = s,$ and 0 otherwise. As in Moneta et al. (2013), we further assume that the innovations $(\varepsilon_1, \ldots, \varepsilon_k)$ in equation (3.1) are independent sources of new information (independent of each other, so an information shock in series 1, say wheat price, is independent of an information shock from series 2, say sorghum price).

Equation (3.1) is termed a structural VAR, as elements of the matrix B_0 are not necessarily all zero. It is of particular interest in this study to know which off diagonal elements are non-zero (structural information). The main reason for this is that we have monthly period of observation (monthly data), and potentially a considerable amount of inter-series interaction, can take place within the month. For instance, wheat price may well affect millet or sorghum prices and these in turn affect conflict events within the month (actually days, but such data are not available).

The model offered in equation (3.1) can be reformed as a standard VAR. This is, perhaps, most easily seen via two steps. First move the contemporaneous value of y_t in equation (3.1) to the left hand side of the equation to get equation (3.2):

$$(I - B_0)y_t = B_1 y_{t-1} + \cdots + B_p y_{t-p} + Bx_t + \varepsilon_t \tag{3.2}$$

Finally merely solve equation (3.2) for y_t. This operation gives us equation (3.3), the reduced form VAR (or subset VAR if the B_i $(i = 1, \ldots, p)$ matrices contain nonzero elements somewhere).

$$y_t = (I - B_0)^{-1}B_1 y_{t-1} + \cdots + (I - B_0)^{-1}B_p y_{t-p} + (I - B_0)^{-1}Bx_t + (I - B_0)^{-1}\varepsilon_t$$

$$= A_1 y_{t-1} + \cdots + A_p y_{t-p} + Ax_t + u_t \tag{3.3}$$

Here $\mathrm{u_t}$ is a vector of white noise innovation process in which its covariance matrix $E(u_t u_t') = \Sigma_u$ is not necessarily diagonal. Notice the innovation vector u_t is now a combination of the original independent shocks ε_t: $u_t = (I - B_0)^{-1}\varepsilon_t = A_0^{-1}\varepsilon_t$.

Our goal is to estimate the reduced form VAR in equation (3.3) and then offer evidence on the particular contemporaneous structural ordering behind the matrix A_0^{-1} . This problem was first described and its solution was hinted at in the paper by Swanson and Granger (1997). Bessler and Akleman (1998) offer the first data-based solution to this task, which followed the suggestions provided in Swanson and Granger (1997).

When specifying the SVAR in this paper, the method of search proposed by Hsiao (1979) using the Hannan-Quinn (Hannan and Quinn 1979) loss criterion will be employed to determine the optimal lag length of each variable in each equation (3.3).[13] Hsiao's method is an iterative procedure to specify the optimal lag length of each variable in each equation separately for more efficient estimations. However, this technique is sensitive to the rank of the importance of the independent variables considered, which rests on prior theory (Kling and Bessler 1985).

The Identification of SVAR

Since the lag structures suggested by the SVAR (equation (3.3)) are usually complex and difficult to interpret, we consider the corresponding vector Moving Average (MA) representation. We follow the presentation in Moneta et al. (2013):

$$y_t = \mu + \sum_{j=0}^{\infty} \varphi_j u_{t-j} = \mu + \sum_{j=0}^{\infty} \varphi_j A_0 A_0^{-1} u_{t-j} = \mu + \sum_{j=0}^{\infty} \Psi_j \varepsilon_{t-j} \qquad (3.4)$$[14]

where the matrix φ_j and $\Psi_j (= \varphi_j A_0)$ represent the moving average parameters and the impulse response from y_t to the shocks ε_{t-j} respectively; μ is the mean of y_t. One advantage of SVAR is to render sufficient information for policy analysis, such as Ψ_j. Thus, it is vital to obtain the matrix A_0, which completes the transformation from u_t (not orthogonal information shocks) to ε_t (orthogonal information shocks). Usually, the constraint that the contemporaneous causal structures among variables of interest $(y_{1t}, y_{2t}, \dots, y_{kt})$ should be acyclic is imposed. This implies that A_0 is lower triangular (Moneta et al. 2013). In the following section, we will summarize a data-based method

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[13] Hannan-Quinn criterion (HQ) is computed as follows: HQ= $\ln|\Sigma| + 2k\ln(\ln T)/T$, where Σ is the estimated non-orthogonal innovations correlation matrix from a first estimated VAR (equation (3.3)), k is the number of parameters fit and T is the number of observations. Other information criteria (Schwarz loss) were also studied and gave similar results.

[14] Note that the exogenous variables (seasonal dummy variables) are excluded from this equation (3.4), suggested by Hsiao-search method when we specify the SVAR model.

to detect the causal structure among the variables in the vector y_t, instead of treating such a structure as a priori determined. Besides this assumption, the non-normality of the innovation terms is also needed in order to make full use of higher-order statistics of the variables.

The Innovation Accounting Techniques

Innovation accounting techniques serve as useful tools to depict the dynamic interaction among variables. One such approach is the impulse response function (IRF), which describes how every series in the system responds to a one-time-only shock in each series. However, considering the case studied in the present paper, a better summary of the moving average representation (equation (3.4)) is the Forecast Error Variance Decompositions (FEVD). FEVD assesses the relative importance of each series (wheat, sorghum, and millet prices and conflict events) on each other at different horizons (distances into the future).The premise of implementing the innovation accounting methods above is orthogonal error covariance. Swanson and Granger (1997) point out that FEVD can only be easily understood regarding to the orthogonalized innovations. To obtain orthogonal innovations, early studies apply a Cholesky factorization to the contemporaneous innovation covariance matrix. Unfortunately, different orderings lead to different conclusions on the innovation accounting analysis (Bessler 1984). An alternative, Bernanke Decomposition approach (Bernanke 1986) is employed in this study, which relaxes the just-identified structure assumption for the VAR residuals. To discover the causal structure among the four variables in contemporaneous time, directed acyclic graphs (DAGs), with the linear non-Gaussian acyclic model (LiNGAM) search algorithm are used.

Linear Non Gaussian Acyclic Model (LiNGAM)

A contemporaneous causal structure reveals the joint distribution of the variables observed as well as measures and forecasts the consequence of drivers (Shimizu et al. 2006). Several search algorithms have been used by contemporary researchers: PC algorithm (Spirtes et al. 2000), Greedy Equivalence Search (GES) algorithm (Chickering 2003), Linear Non-Gaussian Acyclic Model (LiNGAM) algorithm (Shimizu et al. 2006), etc. PC algorithm has been widely used and it assumes Gaussian data in tests of conditional independence. Consequently, it may not be able to identify a unique matrix A_0. GES algorithm relies on variance-covariance to attempt a structural identification of A_0 , leading again to a plethora of observationally equivalent structures (alternative A_0 matrices which cannot be distinguished from one another based on the data). Moreover, the assumption of the Gaussian distributed innovations is usually not the case in most empirical studies (Moneta et al. 2013).

In this paper, we utilize Independent Component Analysis (ICA)-based LiNGAM to discover the causal structure under the assumption behind model in equation (3.4) – no hidden confounders and reduced form innovation terms with non-

Gaussian distributions (Shimizu et al. 2006).[15] The model is presented as follows (following Shimizu et al. (2006)):

$$u_i = \sum_{k(j)<k(i)} b_{ij} u_j + e_i + c_i \tag{3.5}$$

where $u_i, i \in \{1,2,\dots,p\}$ denotes the observed innovations from an estimated form of equation (3.4), which can be organized in a causal order $k(i)$. That is, only the earlier variable could affect the later variable, not vice versa. Coefficient b_{ij} summarizes the causal effect from variable u_j to u_i , e_i represents the non-Gaussian, mutually independent innovations and c_i is constant. The relationship in equation (3.5) can be graphically reflected by a directed acyclic graph (DAG) with vertices u_i and edges – non-zero b_{ij}.

Removing the mean of each variable u_i, then the equation (3.5) can be transformed into the matrix representation:

$$u = Bu + e \tag{3.6}$$

where B represents the coefficient matrix, which could be permutated to strict lower triangular form according to the causal ordering $k(i)$. Denote $A = (I - B)^{-1}$, then

$$u = Ae \tag{3.7}$$

where A could also be permutated to lower triangular form.[16]

[15] In fact, LiNGAM is mainly for the continuous-valued data (Shimizu et al. 2006). Even though the values in the series of conflict events range as integers from 0 to 154, they cover many different values. Thus, still we can manipulate LiNGAM.

[16] Different from "strict lower triangular matrix", some diagonal elements could be zero in low triangular matrix.

Independent component analysis (ICA) (Hyvärinen et al. 2004), a technique of uncovering non-Gaussian hidden factors, plays a crucial role in LiNGAM. Following Shimizu (2014), ICA can be expressed as:

$$u = As \tag{3.8}$$

where u and s stand for the observed variables (u) and the independent components (information shocks). The elements s_j in s are mutually independent latent variables, with non-Gaussian distributions (the independent components).

As a result, the equation (3.7) symbolizes the linear independent component analysis (ICA) model (3.8). ICA makes use of non-Gaussianity to estimate the mixing matrix A given the linear and ample observed data u. Moreover, the fix-point algorithms proposed by Hyvärinen (1999) can be applied to estimate A efficiently, such as 'FastICA' algorithm (Moneta et al. 2013). After obtaining the estimated matrix A, we can calculate the coefficient matrix B. Nonetheless, the order and scaling of the independent components are left to be determined. The detailed operations can be referred to Shimizu et al. (2006) and Shimizu (2014). Finally, knowing the vertex and causal order, we can draw a complete DAG. LiNGAM is an attractive algorithm for the present study since it accommodates non-Gaussian innovations, allowing us to identify complete causal structure without prior knowledge. As will be demonstrated below, our data are highly non-Gaussian.

Data

For this research we use data on commodity prices and conflict events of Sudan from January 2001 to December 2012. The information on wheat, sorghum and millet prices is collected from Global Information and Early Warning System (GIEWS) Food Price Data and Analysis Tool, Food and Agricultural Organization (FAO) of the United Nations. The GIEWS database reports monthly prices of these commodities from the Khartoum port.

The data for the number of conflict events are obtained from Armed Conflict Location & Event Dataset (ACLED) (Raleigh et al. 2010) over the same period. The ACLED database provides disaggregated conflict analysis and crisis in African countries. It collects comprehensive real-time data on political violence in Africa, including the exact dates and locations of conflict events, the types of event, the groups involved, fatalities, and changes in territorial control. The data statistics description is given in Table 3.

Table 3. Summary Statistics on Wheat Price, Sorghum Price, Millet Price and Conflict Events in Sudan; 2001.1 – 2012.12 Monthly Data

Series	Units	Mean	Standard Deviation	Coefficient of Variation
Wheat Price	Sudanese Pound/90kg	98.466	38.109	0.387
Sorghum Price	Sudanese Pound/90kg	74.377	40.418	0.543
Millet Price	Sudanese Pound/90kg	108.250	62.375	0.576
Conflict Events	Number of Conflicts/Month	22.868	21.084	0.922

To present a more direct visual understanding, plots of the time series data are displayed in Figure 3. A common characteristic the price of wheat, sorghum, and millet share is an upward trend, which may indicate that they are not stable. The number of conflict events in Sudan seems stable, except for a peak between 2011 and 2012.

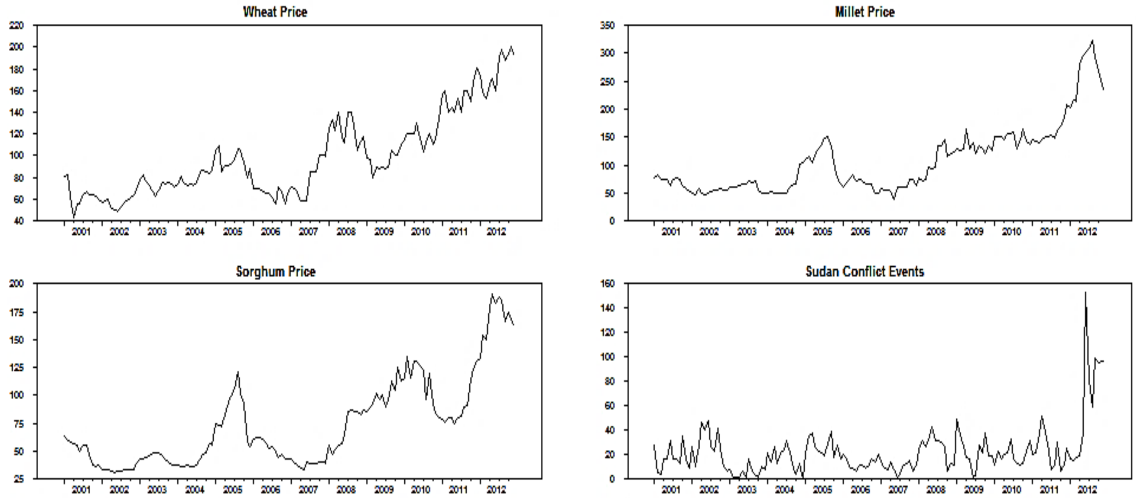

Figure 3. Plots of Wheat Price, Sorghum Price, Millet Price and Conflict Events in Sudan; 2001 - 2012, Monthly Data

Result

Stationarity

VAR model is applied to describe the dynamic interrelationship among stationary variables. That is, any particular variable measured over time should be tied to its mean. Otherwise, it will lead spurious regression if we fail to balance the series' order on the both sides of the equation (Bessler and Kling 1984). Therefore, the first and necessary step in time-series analysis should be to examine if the levels of each series are stationary. One standard unit-root test procedure — Augmented Dickey-Fuller (ADF) test is applied to check whether the four series (wheat price, sorghum price, millet price, and conflict events in Sudan) are stationary or not. The null hypothesis is that there exists a unit root (nonstationary). ADF test statistics suggest that three commodity price series are I(1) at the 5% significance level, while the conflict events in Sudan is I(0). They are consistent with the visual judgment suggested by Figure 3.

Model Specification and Structure Test

The optimal lag length in each equation is chosen by the Hannan and Quinn measure with the Hsiao-Search method. Regression Analysis of Time Series (RATS) software is implemented for the estimation of SVAR model. However, according to the plots of the innovations from the estimation of SVAR, we find some jumps in the conflict events series between 2011 and 2012 (which indicates potential heterogeneity). Therefore, a structural breakpoint during this period (January 2001 – December 2012) is possible, which may be due to the regime changes occurring in Sudan (July 2011).In order to test this hypothesis, the Bai and Perron (1998, 2003) procedures are applied. As a result, the "conflict events" series suggest a structural break in September, 2011, where we also observe a peak in the corresponding innovation series. Additionally, the other three series do not indicate the necessity of any breakpoints. Interestingly, the 95% confidence interval provided by the Bai-Perron test ranges from July 2011 to October 2011, which is consistent with regime changes in Sudan.[17]

Estimation Results of SVAR

With the same techniques (Hsiao search algorithm with H&Q criteria), the optimal lags for each equation are selected and the results are presented in Table 4 to Table 7.

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[17] South Sudan seceded from Sudan on July 9, 2011, which is likely to influence the structural of the conflict events time series.

Table 4. Hsiao Search on Specification of Wheat Price

HQ	Constant	Seasonal Dummies	Lags of Wheat Price				Lags of Sorghum Price				Lags of Millet Price				Lags of Conflict Events			
			-1	-2	-3	-4	-1	-2	-3	-4	-1	-2	-3	-4	-1	-2	-3	-4
6.701	X																	
6.974	X	X																
4.600*	X		X															
4.623	X		X	X														
4.610	X		X	X	X													
4.635	X		X	X	X	X												
4.626	X		X				X											
4.653	X		X				X	X										
4.672	X		X				X	X	X									
4.698	X		X				X	X	X	X								
4.622	X		X								X							
4.646	X		X								X	X						
4.668	X		X								X	X	X					
4.655	X		X								X	X	X	X				
4.618	X		X												X			
4.644	X		X												X	X		
4.660	X		X												X	X	X	
4.673	X		X												X	X	X	X

Each row represents an alternative specification of the dynamic representation of wheat price (in current time) as a function of a constant only, a constant and 11 seasonal dummy variables, a constant and lags of wheat price, sorghum price, millet price or conflict events. HQ represents Hannan and Quinn criteria. We select that model specification that minimizes HQ. We report only four lags of each variable here, in actuality we search over twelve lags of each. All HQ measures on the unreported lags are higher than metrics shown in the table. An asterisk (*) indicates minimum.

Table 5. Hsiao Search on Specification of Sorghum Price

HQ	Constant	Seasonal Dummies	Lags of Sorghum Price				Lags of Millet Price				Lags of Wheat Price				Lags of Conflict Events			
			-1	-2	-4	-5	-1	-2	-3	-4	-1	-2	-3	-4	-1	-2	-3	-4
6.756	X																	
7.037	X	X																
4.313	X		X															
4.313	X		X	X														
4.290	X		X	X	X													
4.290[18]*	X		X	X	X	X												
4.297	X		X	X	X	X	X											
4.322	X		X	X	X	X	X	X										
4.342	X		X	X	X	X	X	X	X									
4.354	X		X	X	X	X	X	X	X	X								
4.298	X		X	X	X	X					X							
4.325	X		X	X	X	X					X	X						
4.317	X		X	X	X	X					X	X	X					
4.310	X		X	X	X	X					X	X	X	X				
4.314	X		X	X	X	X									X			
4.341	X		X	X	X	X									X	X		
4.337	X		X	X	X	X									X	X	X	
4.364	X		X	X	X	X									X	X	X	X

Each row represents an alternative specification of the dynamic representation of sorghum price (in current time) as a function of a constant only, a constant and 11 seasonal dummy variables, a constant and lags of wheat price, sorghum price, millet prices or conflict events. HQ represents Hannan and Quinn criteria. We select that model specification that minimizes HQ. We report only four lags of each variable here, in actuality we search over twelve lags of each. All HQ measures on the unreported lags are higher than metrics shown in the table. An asterisk (*) indicates minimum.

[18] It is 4.2895 if four digits are kept. Thus, it is the minimum.

Table 6. Hsiao Search on Specification of Millet Price

HQ	Constant	Seasonal Dummies	Lags of Millet Price				Lags of Sorghum Price				Lags of Wheat Price				Lags of Conflict Events			
			-1	-2	-3	-4	-1	-2	-3	-4	-1	-2	-3	-4	-1	-2	-3	-4
7.375	X																	
7.649	X	X																
4.999	X		X															
5.012	X		X	X														
5.036	X		X	X	X													
5.061	X		X	X	X	X												
5.014	X		X				X											
5.020	X		X				X	X										
5.038	X		X				X	X	X									
5.065	X		X				X	X	X	X								
4.979*	X		X								X							
5.005	X		X								X	X						
5.013	X		X								X	X	X					
4.990	X		X								X	X	X	X				
5.005	X		X								X				X			
5.030	X		X								X				X	X		
5.031	X		X								X				X	X	X	
5.048	X		X								X				X	X	X	X

Each row represents an alternative specification of the dynamic representation of millet price (in current time) as a function of a constant only, a constant and 11 seasonal dummy variables, a constant and lags of wheat price, sorghum price, millet price or conflict events. HQ represents Hannan and Quinn criteria. We select that model specification that minimizes HQ. We report only four lags of each variable here, in actuality we search over twelve lags of each. All HQ measures on the unreported lags are higher than metrics shown in the table. An asterisk (*) indicates minimum.

Table 7. Hsiao Search on Specification of Conflict Events

HQ	Constant	Seasonal Dummies	Lags of Conflict Events				Lags of Wheat Price				Lags of Sorghum Price				Lags of Millet Price			
			-1	-2	-3	-4	-1	-2	-3	-4	-1	-2	-3	-4	-1	-2	-3	-4
4.981	X																	
5.208	X	X																
4.571	X		X															
4.597	X		X	X														
4.617	X		X	X	X													
4.641	X		X	X	X	X												
4.550*	X		X				X											
4.571	X		X				X	X										
4.597	X		X				X	X	X									
4.618	X		X				X	X	X	X								
4.574	X		X				X				X							
4.585	X		X				X				X	X						
4.611	X		X				X				X	X	X					
4.632	X		X				X				X	X	X	X				
4.573	X		X				X								X			
4.600	X		X				X								X	X		
4.625	X		X				X								X	X	X	
4.623	X		X				X								X	X	X	X

Each row represents an alternative specification of the dynamic representation of conflict events (in current time) as a function of a constant only, a constant and 11 seasonal dummy variables, a constant and lags of wheat price, sorghum price, millet price or conflict events. HQ represents Hannan and Quinn criteria. We select that model specification that minimizes HQ. We report only four lags of each variable here, in actuality we search over twelve lags of each. All HQ measures on the unreported lags are higher than metrics shown in the table. An asterisk (*) indicates minimum.

Then, we regress the SVAR model again from January 2001 to September 2011, with robust variance-covariance matrix considering the possible heteroscedasticity.[19] The estimation results of the SVAR model specified above are listed in Table 8.

According to Table 8, each variable's own one period lag could exert statistically significant and positive effect on itself at the 1% level. Wheat price shows up significantly (5% level) in the millet price equation, whereas it is not the case for the other commodity prices in some other price series. In terms of the relationship between commodity prices and conflict events, only one period lagged wheat price has a significantly positive effect on the number of conflict events in Sudan. These results seem to suggest that wheat price is the most significant in this particular system. We will take advantage of the innovation techniques shown below to depict the dynamic relationship among the variables of interest.

[19] We also estimate the same model from 2001.1 to 2011.7, and from 2001.1 to 2011.10, which were the confidence limits of the 95% level (i.e., the lower and upper boundaries of the confidence interval) suggested by the Bai-Perron test. The results are not reported here but available upon request.

Table 8. Estimate Result on SVAR, 2001.1 – 2011.9, Monthly Data

Dependent Variable		Variable	Coeff	Std. Error	T-Stat	Signif
Wheat Price (WT)	1	Constant	4.758	3.016	1.578	0.115
	2	WT{1}	0.957	0.037	26.083	0.000
Sorghum Price (SOR)		Variable	Coeff	Std.Error	T-Stat	Signif
	1	Constant	3.238	1.662	1.948	0.051
	2	SOR{1}	0.827	0.131	6.298	0.000
	3	SOR{2}	0.381	0.162	2.348	0.019
	4	SOR{3}	-0.086	0.195	-0.439	0.660
	5	SOR{4}	-0.329	0.123	-2.666	0.008
	6	SOR{5}	0.164	0.108	1.514	0.130
Millet Price (MIL)		Variable	Coeff	Std.Error	T-Stat	Signif
	1	Constant	-1.277	2.665	-0.479	0.632
	2	WT{1}	0.144	0.070	2.050	0.040
	3	MIL{1}	0.883	0.058	15.160	0.000
Conflict Events (CE)		Variable	Coeff	Std.Error	T-Stat	Signif
	1	Constant	1.785	3.212	0.556	0.579
	2	WT{1}	0.078	0.039	2.009	0.045
	3	CE{1}	0.544	0.075	7.290	0.000

The plots of the innovations derived from the SVAR above are presented in Figure 4. Additionally, applying ADF test on these innovations suggests that all the residual series are stationary.

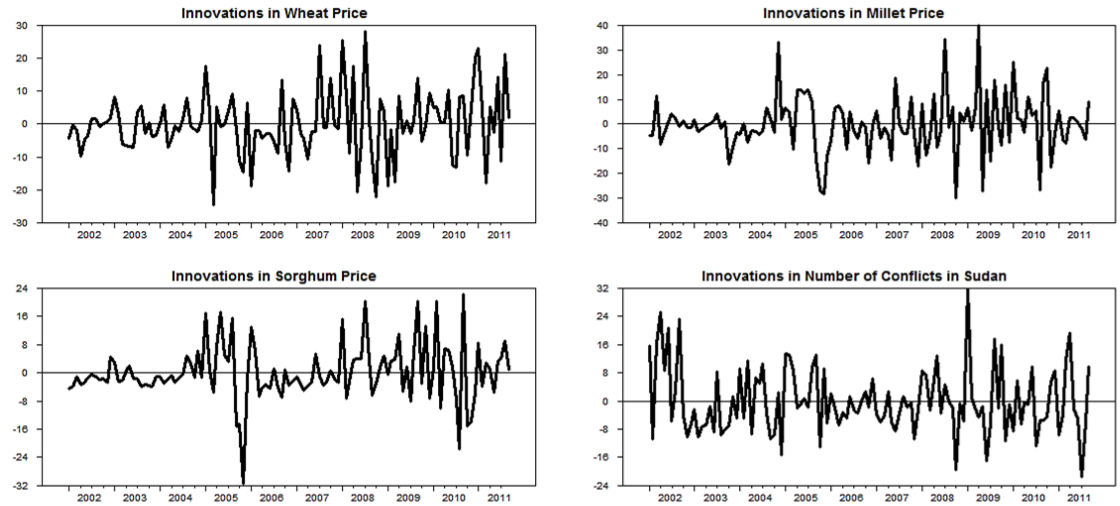

Figure 4. Plots on Innovations from a SVAR on Wheat Price, Sorghum Price, Millet Price and Conflict Events; 2001.1 – 2011.9, Monthly Data

Directed Acyclic Graphs (DAGs) Results

DAGs are employed to discover the causal flows on the contemporary innovations from the SVAR (January 2001 – September 2011) above. DAGs are available in the software TETRAD V (Ramsey et al. 2013). We fit the models summarized from Table 4 to Table 7 equation by equation using Ordinary Least Squares (OLS) and a system using Seemingly Unrelated Regressions (SUR). The innovations from each procedure are quite similar and most importantly, the graph structures from both OLS and SUR innovations are the same.

Normality Test Results

To decide the specific search algorithm for analyzing our estimated innovations, we investigate if the innovations (errors) follow Gaussian distributions. PC (or GES) algorithm requires that the residuals from the SVAR model are Gaussian distributed (normal distributed), whereas LiNGAM assumes that at most one residual follows Gaussian distribution. Therefore, normality tests including skewness test, kurtosis test, and Jarque-Bera test (Jarque and Bera 1980, 1987) are executed for each innovation series derived from the SVAR. The Jarque-Bera test statistic is chi-squared distributed with two degrees of freedom under the null hypothesis that the data are normally distributed (i.e., for normal distribution, skewness is 0 and kurtosis is 3, or equivalently the excess kurtosis is 0). We present the test for normality results in Table 9.

From Table 9, we observe that skewness statistics do not exhibit strong evidence of significant asymmetric property (only the innovations of the conflict events reject the null hypothesis at the 1% significance level); the kurtosis statistics indicate peaks for only in sorghum and millet price innovation series at the 1% significance level. Finally, and most importantly, all of the Jarque-Bera test statistics, considering both skewness and kurtosis together, exceed the critical value at the 1% significance level, except the residuals from the wheat price (at the 10% significance level). The normality tests suggest that each innovation series has non-normal distribution, albeit the relatively weak evidence for the non-Gaussian distribution in wheat price innovations. Therefore we use LiNGAM search algorithm to explore the contemporaneous causal structure.[20]

[20] In fact, in the case of unique Gaussian component, the model can still be estimated with LiNGAM given that the exclusive Gaussian part cannot interact with any other components with non-Gaussian distribution (Hyvärinen et al. 2004).

Table 9. Normality Tests for the Innovations, 2001.1 – 2011.9 Monthly Data

Variables	Skewness[21]	Kurtosis (excess)[22]	Jarque-Bera[23]
	(P-Value)	(P-Value)	(P-Value)
Wheat Price	0.297	0.873	5.431
	(0.196)	(0.061)	(0.066)
Sorghum Price	0.070	2.872	40.294
	(0.761)	(0.000)	(0.000)
Millet Price	0.341	1.927	20.380
	(0.137)	(0.000)	(0.000)
Conflict Events	0.721	0.745	12.832
	(0.002)	(0.111)	(0.002)

LiNGAM Algorithm Results

The DAG found summarizing the causal structure for the four variables is displayed in Figure 5.[24] New information stemming from commodity market has an effect on conflict situation in Sudan: the innovations of wheat price could affect innovations in conflict events through sorghum price. Figure 5 also indicates that wheat price is exogenous. Wheat price will influence the innovations in other cereal prices and conflict events in Sudan directly or indirectly, indicating that wheat market is the dominant market. In addition, among the three commodity prices, directed edges (information flows) are also observed from wheat price to millet price and from sorghum

[21] Skewness test is a test of symmetry of the probability distribution of a random variable (the null hypothesis is skewness: 0).

[22] Krutosis test is a test of peakedness of the probability distribution of a random variable (the null hypothesis is kurtosis = 3 or excess kurtosis = 0).

[23] Jarque-Bera test is a normality test of innovations, taking into account of both skewness and kurtosis. Details can refer to Jarque and Bera (1980, 1987).

[24] The graph structure is found using LiNGAM algorithm found on the Carnegie Mellon, Department of Philosophy, TETRAD homepage: http:///www.phil.cmu.edu/projects/tetrad

price to millet price. The positive relationship is given on each arrow, indicating that cereals are substitutes.

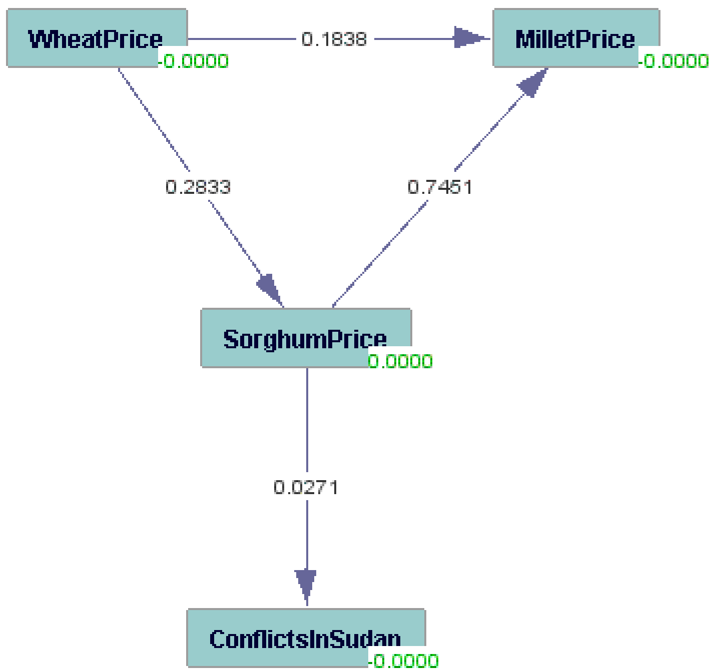

Figure 5. Pattern of Causal Flow among Innovations in Wheat Price, Sorghum Price, Millet Price and Conflict Events Based on LiNGAM, SVAR

Forecast Error Variance Decompositions (FEVD)

With the contemporary causal relationships displayed above (Figure 5), we perform Bernanke factorization (see Estima's description of this software procedure embedded in RATS (Doan 2010)). The corresponding FEVD results are shown in Table 10. The uncertainty in each series at horizons 0, 1, 2 and 12 months ahead is measured as the column labeled "Standard Error". This measure is accounted for by innovations in each series. We label each series' contribution under the columns headed by the label "Due To". The sum of entries in any row is 100 (allowing rounding errors). For example, looking ahead 12 months, all of the uncertainty in Conflict Events is accounted for by variation in Conflict (87.215%), Wheat Price (12.745%), Sorghum Price (0.040%), and Millet Price (0.000%). So wheat price shocks account for part of the uncertainty in Conflict Events at the 12-month horizon.

Table 10. Percentage of Forecast Uncertainty Accounted for by Innovations from a SVAR in Each Series at Horizons 0, 1, 2, and 12 Months Ahead

Horizon (Months Ahead)	Standard Error	Due to: Wheat Price	Due to: Sorghum Price	Due to: Millet Price	Due to: Conflict Events
			(Wheat Price)		
0	9.708	100.000	0.000	0.000	0.000
1	13.439	100.000	0.000	0.000	0.000
2	16.116	100.000	0.000	0.000	0.000
12	27.656	100.000	0.000	0.000	0.000
			(Sorghum Price)		
0	7.880	12.181	87.819	0.000	0.000
1	10.223	12.181	87.819	0.000	0.000
2	13.223	12.181	87.819	0.000	0.000
12	24.599	12.181	87.819	0.000	0.000
			(Millet Price)		
0	11.581	10.958	22.575	66.467	0.000
1	15.814	15.006	21.549	63.445	0.000
2	18.803	19.336	20.451	60.213	0.000
12	33.712	54.143	11.626	34.231	0.000
			(Conflict Events)		
0	9.345	0.006	0.046	0.000	99.948
1	10.670	0.561	0.045	0.000	99.394
2	11.084	1.608	0.045	0.000	98.347
12	11.926	12.745	0.040	0.000	87.215

The uncertainty in each series at horizons 0, 1, 2 and 12 months ahead is measured as the column labeled “Standard Error”. This measure is accounted for by innovations in each series. We label each series’ contribution under the columns headed by the label “Due To”. The sum of entries in any row is 100 (allowing rounding errors). For example, looking ahead 12 months, all of the uncertainty in Conflict Events is accounted for by variation in Conflict Events 87.215%, Wheat Price, 12.745%, Sorghum Price, 0.040% and Millet Price, 0.000%. So Wheat Price shocks account for part of the uncertainty in Conflict Events at the 12-month horizon.

Forecast error variance decomposition (FEVD) illustrates how much of the variation in one variable at horizon $t + s$ can be accounted by the innovations in each variable at horizon t. Due to the space, we only present the FEVD at horizon 0 (contemporaneous time), 1, 2, 12 months ahead (i.e., $s = 0, 1, 2, 12$). Generally, within a short period (e.g., 0, 1 or 2 months), each variable can be almost explained by the shocks from its own history, such as wheat price (100%), sorghum price (87.819%), millet price (66.467%), and conflict events (99.948%) in contemporaneous time. However, moving to a longer run (12 months), other variables play a more important role in explaining the variation in their uncertainty. For instance, wheat price explains as much as 54.143% of the price variation in millet at the 12-month horizon, which is much higher than the portion it explains in contemporaneous time (10.958%).

Specifically, wheat is exogenous throughout the12 month horizon, since 100% of price volatility can be accounted by innovations in its own market, regardless of horizons. Relatively, sorghum is less exogenous, in that around 12% of price volatility is explained by innovations in the wheat market. In terms of millet, approximately two thirds of its price volatility is attributed to information arising in wheat and sorghum markets. At the horizon of 12 months, wheat will account for majority (more than half) of the volatility in millet price. The volatility of conflict events in Sudan is primarily explained by itself and wheat price (volatility of sorghum price can explain a very small part of conflict uncertainty, around 0.045%). Moreover, wheat price will display a greater influence on the incidence of conflict events in Sudan as the horizon increases. In sum, the interaction between commodity prices and conflict centers on the interface between wheat price and conflict events in Sudan.[25]

Conclusion and Discussion

In this paper, we attempt to discover the interaction among three major cereal prices (wheat, sorghum, and millet) and the onset of conflict events in Sudan, with Structure Vector Autoregression (SVAR). Normality tests applied to informational innovations suggest that the Linear Non-Gaussian Acyclic Model (LiNGAM) can be executed to identify contemporaneous causal structures. The combination of these methods enables us to identify the dynamic interaction among three cereal markets and conflict events. Specifically, the Directed Acyclic Graphs (DAGs) and the innovation accounting techniques (FEVD) suggest that the only linkage between commodity prices and conflict events is the shocks from the wheat market on conflict levels, through the sorghum market. This impact persists for almost two years, even though it decreases over time. Interestingly, as well, we find no feedback from conflict to commodity prices.

The cereal consumption patterns in Sudan may provide a plausible explanation of the causal path uncovered here. Historically sorghum has been the most popular staple food of Sudan. In recent years, consumer preferences, especially in urban and peri-urban areas have shifted to wheat (Abdelrahman 1998; Mustafa et al. 2013; Jayne et al. 2010). In the absence of proportional increase in production of wheat, imports have been the primary means of meeting this access demand of wheat. Consequently, the net price of

[25] Results from Vector Error Correction Model (VECM) are consistent with SVAR that cereal prices do move conflict, while VECM indicates millet price is the driver of conflict instead of wheat price. Perhaps the different results based on different models are due to our modest sample size (144 observations).

wheat has also increased. Our empirical results of contemporaneous effects show the consequences of this phenomenon. We find that rising wheat price causes sorghum price to increase (perhaps due to the weak substitution effects). Our graphical representation illustrates that the increase in the cereal prices causes a surge of conflict outbreaks. In addition, structural analysis of the data (January 2001 – December 2012) suggests a potential breakpoint in September 2011. This coincides with the regime change as Sudan after July 2011 was separated from its southern part.

Considering these results, we offer some policy perspectives and suggestions. As imported commodities such as wheat obtains more popularity in Africa, the concern regarding self-sufficiency is often disregarded on free market and trade grounds. However, policy makers should not ignore that often times African countries lack conditions necessary for such an environment (Letiche 2010). Policies including subsidy and price regulation may help lower the onset of conflict events to some extent. Programs enhancing domestic production of wheat (such as introducing advanced technology) are possibly a more sustainable solution. As Mustafa et al. (2013) point out, "Wheat production has consistently been supported by government interventions either through subsidized inputs or price setting, however, it rarely exceeds 20 percent of the domestic requirement (some 1.8 million MT) and the remaining 80 percent is imported (FAO/WFP 2011)." If high food prices act as a catalyst for conflict, lowering or keeping reasonable food prices and supply with effective policy could reduce the incidence of conflict and stabilize countries. A caveat has to be made here. Despite the multifaceted and complex links between conflict and commodity prices, we cannot conclude that one is the other’s necessary or sufficient condition, taking into consideration many other potential factors. Still, our results suggest that cereal prices play a vital role in conflict onset. Moreover, in order to promote peace-building and to mitigate conflict, controlling wheat price may have an effect in the Sudanese context.

CHAPTER IV

EXPLORING THE EFFECTS OF TERRORISM ON CEREAL DEMAND IN SUDAN

Introduction

Basic Introduction about Sudan

Sudan is the third largest country in Africa. About 80 percent of the population are dependent on agriculture for their livelihood. Additionally, agriculture makes up 90 percent of non-oil export earnings (Abdelrahman 1998). Cereal crops serve as a vital calorie source in the diet (Abdelrahman 1990). Sudan has been suffering from conflict including terrorism for most of its history. The impacts of terrorism are reflected in both direct human, commodity and infrastructure damages and in long-term effects on local economy. Sudanese face ongoing threats, uncertainty, and fears from terrorism. Such a situation can affect food demand and this will be explored herein.

Cereals as a Food Source in Sudan

Sorghum, millet, and wheat are the three main cereals in Sudan, providing around 60 percent of country level cereal consumption (Hamid 2003). Sorghum is the main staple food in the northern part of the country with millet being that in western Sudan. Wheat is an important diet component for which demand is growing particularly in northern Sudan (FEWS NET 2012). In recent years, Sudan has had a surplus of sorghum and has been self-sufficient in millet, but Sudan produced much less wheat than was consumed (Osman 1989) with increasing imports over time rising to as much as 75 percent of the wheat consumed between 2000 to 2010 (Miustafa 2013). Furthermore, growth in domestic wheat production is slower than consumption growth, with production technology and environmental conditions the likely causes (Ageeb 1994).

Donors have been willing to provide food aid in form of wheat or wheat flour, in order to reduce the domestic cereal deficit and help rural development. Terrorism incidents have also tended to increase donor wheat aid and consumption. The increased domestic wheat consumption and dependency on imports forms a “dilemma” for domestic policy and foreign aid institutions. Wheat imports have been costly and worsened Sudan’s negative trade balance (Hassan and Faki 1993). The country also contains a large population component that is food insecure and this is expected to continue during the next decade with the wheat deficit contributing (Elmulthum et al. 2011).

Policy debates about reducing Sudan’s high dependence on imported wheat have lasted for many years, centering on pricing mechanisms and domestic production enhancements. Ali (1998) asserts that the domestic resources for wheat production should be fully exploited to bridge the gap. Sudan has stated plans to expand the land devoted to wheat production by 25 percent each year, targeting wheat self-sufficiency in five years’ time (Mazen 2010), but that has not fully happened to date. In addition, some scholars recommend the allocation of substantial financial resources to enhance food production by investing in agricultural technology, education, agricultural extension, and infrastructure (Elmulthum et al. 2012). Additionally, Ibraheim (1996) indicates that food aid while stabilizing domestic consumption has a negative effect on the achievement of self-sufficiency.

Theoretical Motivation

Nzuma and Saeker (2010) argue that an understanding of food demand determinants and associated price elasticities allows policymakers to design effective and efficient policies. Sadoulet and de Janvry (1995) claim that elasticity estimates play an essential role for future business investment. Moreover, the identification of dynamic relationships among the set of variables involved with demand could provide insights for policy-making. Previous demand research has concentrated on estimating the relationship between prices and quantities sometimes incorporating demographic factors (Dudek 2010; Davis et al. 2011). In Sudan, terrorism is an important demographic factor. It affects household consumption patterns, income, market function, personal security, and costs of living among other factors. Numerous studies have examined the macroeconomic effects of terrorism (Abadie and Gardeazabal 2003, 2008), but to our knowledge none have explored the influence of terrorism on food demand. Therefore, this paper will attempt to bridge the gap by incorporating the effects of terrorism into demand estimation for three major cereals (sorghum, millet, and wheat) in Sudan. This will be examined using both an Almost Ideal Demand System (AIDS) model and a Directed Acyclic Graph (DAG). Moreover, to better understand the cereal demand situation, we utilize both AIDS and DAG models to predict the three cereal consumption shares in Sudan, and compare their forecast performance to identify a model with better forecast.

Estimation Strategy

To carry out the estimation, a widely used static demand system – the AIDS model and a DAG approach are employed. The AIDS model is selected because of its common usage in empirical demand analysis (Buse 1994). Nevertheless, there may exist the problem of endogeneity that may bias the results. Specifically, the three cereal prices are highly likely to be correlated with each other, given that they are primary calories sources for the Sudanese population. Consequently, DAGs are utilized to circumvent that problem (Akleman et al. 1999). When estimating the DAG, we implement the following procedures. The first step is to explore if the levels of each series are stationary using the Augmented Dickey-Fuller (ADF) test. The second step is to determine the optimal lag length based on Hannan and Quinn loss metrics using a maximum of four lags in levels and three for first differences as recommended by Wang and Bessler (2003). The third step is to use the TETRAD V software to get the graphical models.

In what follows, we examine the forecast performance of the AIDS model (with and without the theoretical homogeneity or symmetry constraints) and the DAG model with several criteria. To achieve this goal, we estimate the three models during the period 1970 – 2000. Then rested upon the estimations, we generate one-step-ahead and two-step-ahead out of sample forecasts from 2001 to 2012 recursively. Additionally, encompassing tests are implemented to determine which model encompasses another one.

Data

The dataset that will be used herein consists of yearly observations on Sudanese consumption and prices from 1966 to 2012, for wheat, sorghum and millet coupled with terrorism data.[26] These commodities constitute about 70% of the calories gained by individuals in Sudan (Elmulthum 2007).

Data on total domestic consumption were obtained from IndexMundi.[27] Cereal prices were assembled from three databases: Datamarket for 1966-2006, FAO Statistics (FAOSTAT) for 2007-2011, and the FAO Global Information and Early Warning System (GIEWS) for 2012. The price series are current local currency units (LCU) per tonne. In addition, the price in 2012 is formed from a monthly weighting of wholesale prices. Annual expenditures are derived by multiplying quantities and prices and then adding up all the individual cereal crop expenditures. With respect to expenditure share of each cereal, they are obtained by dividing the total expenditure by the individual cereal expenditure.

Data about terrorism come from the Global Terrorism Database (GTD) that is developed by START (2013). GTD defines a terrorist event as, "the threatened or actual use of illegal force and violence by a non-state actor to obtain a political, economic, religious, or social goal through fear, coercion, or intimidation" (START 2013). For

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[26] The data on terrorism events span from 1970 to 2012. All the other series start from 1966 and end in 2012.

[27] Here we add up the commodity use for food, seed, and industrial uses (FSI) as the measure of total domestic consumption. The unit of measurement is 1000 MT (metric tonnes or tonnes). "IndexMundi is a data portal that gathers facts and statistics from multiple sources and turns them into easy to use visuals." Please refer to http://www.indexmundi.com/about.html for more information.

each terrorism incident documented, GTD offers details on the exact date, location, targets and perpetrators, weapons used, among other items. In this study, we use the annual count of such terrorist events to capture the frequency characteristics.

Model Specification

Almost Ideal Demand System (AIDS)

The Deaton and Muellbauer (1980) formulation for an Almost Ideal Demand System (AIDS) model is:

$$w_{it} = \alpha_i + \sum_{j=1}^{N} \gamma_{ij} ln\, p_{jt} + \beta_i ln(X_t/P_t) + u_{it},\ \ i = 1, \ldots, N; t = 1, \ldots, T. \quad (4.1)$$

where *N* is the number of commodities in the system; T is the number of time periods; w_{it} represents the expenditure share of the *i*-th commodity at time *t*, that is $w_{it} = p_{it} * q_{it}/X_t$ with p_{it} and q_{it} being the price and quantity consumed for the *i*-th commodity at time *t*, and X_t being the total consumption expenditure on all of the *N* commodities at time *t*; $\alpha_i, \beta_i, \gamma_{ij}$ are the parameters to be estimated. P_t is the price index at time *t*, which is defined as follows:

$$lnP_t = \alpha_0 + \sum_{j=1}^{N} \alpha_j lnP_j + \frac{1}{2} \sum_{i=1}^{N} \sum_{j=1}^{N} \gamma_{it} lnP_{it} lnP_{jt}\,,\ \ t = 1, \ldots, T. \quad (4.2)$$

The price index above makes the system non-linear, which complicates the estimation process. To simplify estimation, Deaton and Muellbauer (1980) suggest use of a linear, Stone's price index:

$$lnP_t = \sum_{i=1}^{N} w_{it} lnp_{it} \quad (4.3)$$

The corresponding equation is referred to as the linear approximate/almost ideal demand system (LA/AIDS). However, this simplified approximation for P_t brings about another problem – simultaneity, since two variables w_{it} and P_t are codetermined.

In this context, the coefficients can be easily interpreted: α_i stands for the consumption of the $i-th$ commodity; β_i reflects the change in the $i-th$ commodity's expenditure share with respect to the percentage change in real income holding all the other variables constant; γ_{ij} indicates the change in the $i-th$ commodity's expenditure share stimulated by a one percent change in the $j-th$ commodity's price holding all the other variables constant.

To estimate the effects of terrorism on demand, we add a variable identifying extent of terrorism into the basic AIDS model (i.e., equation (4.1)) as follows:

$$w_{it} = \alpha_i + \sum_{j=1}^{N} \gamma_{ij} ln\, p_{jt} + \beta_i ln(X_t/P_t) + \theta_i lnZ_t + u_{it},\ \ i = 1, \dots, N; t = 1, \dots, T. \tag{4.4}$$

where Z_t is the number of terrorism incidents in time *t*; θ_i are the parameters to be estimated, representing the change in the $i-th$ commodity's expenditure share with respect to the percentage change in number of terrorism events.

The theoretical restrictions on the parameters of equation (4.1) are:

Adding-up: $\sum_{i=1}^{N} \alpha_i = 1,\ \ \sum_{i=1}^{N} \beta_i = 0,\ \ \sum_{i=1}^{N} \gamma_{ij} = 0 \quad j = 1,2, \dots, n.$ (4.5)

Homogeneity: $\sum_{j=1}^{N} \gamma_{ij} = 0 \quad i = 1,2, \dots., n.$ (4.6)

Symmetry: $\gamma_{ij} = \gamma_{ji} \quad\quad for\ i \neq j.$ (4.7)

It is well acknowledged that the restrictions (4.5) (i.e., the adding up constraint) are part of a maintained hypothesis of any demand system (Deaton and Muellbauer 1980) and can be imposed by not estimating one of the equations. Thus, one only needs to test the restrictions implied by homogeneity (4.5) and symmetry (4.6).

The Marshallian (uncompensated) demand elasticities from the linearized model are expressed as follows (Green and Alston 1990):

Income elasticity: $\eta_i = 1 + \beta_i / w_i$ (4.8)

Price elasticity: $\varepsilon_{ij} = -\delta_{ij} + (\gamma_{ij} - \beta_i w_j)/w_i$, where $\delta_{ij} = 1, if\ i = j; 0, otherwise.$

(4.9)

Since the AIDS model originates from a coherent analytical framework, it's relatively easy to estimate and interpret. However, the underlying assumption of the AIDS model is that consumption is always in equilibrium, which does not usually hold in most empirical cases. For instance, changing preferences or habits, incomplete information, and adjustment to the exogenous shocks to prices and income can lead to short term disequilibrium in consumption. It is probably one of the reasons why most static LAIDS models do not satisfy the theoretical restrictions (Duffy 2003). Furthermore, AIDS models assume that prices of the three major cereals are independent of each other, which is in conflict with our knowledge in Sudan. We will also use a DAG approach to overcome these limitations of the AIDS model.

Directed Acyclic Graphs (DAGs)

Following Bessler and Loper (2001), a directed graph represents the causal relationship among a set of variables. More rigorously, it consists of an ordered triple $< \boldsymbol{V}, \boldsymbol{M}, \boldsymbol{E} >$. Therein, $\boldsymbol{V}$ stands for a nonempty set of vertices (variables); $\boldsymbol{M}$ is a nonempty set of marks (i.e., symbols attached to the end of undirected edges); $\boldsymbol{E}$ represents a set of ordered pairs. Every element in the set $\boldsymbol{E}$ is termed as an edge. If vertices (variables) are connected by an edge, then we say they are adjacent. A directed acyclic graph is a directed graph without directed cyclic paths.

In recent years, based on different assumptions of data series, multiple search algorithms have been proposed to build directed acyclic graphs that reveal causal structures based on how certain data change over time, including Gaussian-innovation based algorithms, non-Gaussian-innovation based algorithms, and the like. That is, the fundamental assumptions of innovations distributions differentiate those methods. To do this, the commonly used methods are the PC algorithm (Spirtes et al. 2000) and Greedy Equivalence Search (GES) algorithm (Chickering 2003), which are Gaussian-innovation based methods. Additionally, the linear Non-Gaussian Acyclic Model (LiNGAM) algorithm (Shimizu et al. 2006) is usually utilized to manipulate non-Gaussian innovations. As will be displayed in the later session, a majority of our data series follow Gaussian distributions. Thus the PC and GES algorithms therefore will be employed to discover the DAG and embodied causal structure.

The PC algorithm starts from unrestricted relationships among variables of interest (i.e., any two variables are connected with undirected edges). Then edges between variables are removed stepwise to remove cases where there are not "causal flows" where the items exhibit zero correlation or partial correlation (conditional correlation) (Akleman et al. 1999). Note that the conditioning variable(s) on the deleted edges between two variables is termed as the sepset of those variables (the sepset is empty for vanishing zero-order conditioning information) (Bessler and Loper 2001). For more detailed description of PC algorithms, please refer to Spirtes et al. (2000). A caveat has to be made before proceeding. The significance level plays a critical role in implementing PC algorithms to obtain graphically causal structure. Spirtes et al. (2000) explain the setting of the significance levels plainly, "…the significance level used in making decisions should decrease as the sample sizes increase, and the use of higher significance levels (e.g., 0.2 at the sample sizes less than 100, and 0.1 at sample sizes between 100 and 300) may improve performance at small sizes." As a result, we set the significance level to 0.2, taking into account that our sample size is less than 100.

The GES algorithm is a two-stage search algorithm that uses scoring criteria to build the DAG. In contrast to the PC algorithm, GES begins with an utterly independent (disconnected) graph and then proceeds to add edges (or reverses edge direction) for which the Bayesian posterior score is improved the most. This process is repeated until no additional edges or reverse directions can be added which improve the score. On the basis of the result of the first stage, the second stage is to implement the algorithm backwards. That is, edges are removed or directions are reversed if such changes raise the Bayesian posterior score. Similarly, this stage continues until no higher score emerges. Chickering (2003) provides a thorough and clear description of GES algorithm and its implementation.

Edges or directions that remain robust in both algorithms may be considered to be in a higher level of confidence, compared with cases that edges or directions change across the two algorithms (Zhang et al. 2006).

Estimation Results and Discussion

Estimation of the AIDS Model

Two AIDS demand models (i.e., with and without the “terrorist attack” variable), will be formed following the steps:

- estimate the parameters of demand system for wheat, sorghum, and millet in Sudan;
- test the restrictions of homogeneity and symmetry;
- calculate the elasticities based on the parameters estimated and constraints tested.

A caveat has to be made here. One underlying assumption is weak separability from other commodities, including food and non-food. Therefore, the choices and preferences within the three cereals are assumed to be independent of price changes of other goods.

To avoid singularity in the covariance matrix, the millet equation is dropped during estimation. The whole system is unchanged, regardless of which equation is ignored. In addition, the parameters in the dropped equation (i.e., millet equation) can be derived from the adding-up constraint.

We present the consequent empirical estimates for AIDS models with/without the “terrorist attack” variable in Table 11 including the associated standard errors.

Table 11. Regression Results of AIDS

Independent Variable	Wheat		Sorghum		Millet	
	Status of the "terrorist attack" variable inclusion					
	Excluded	Included	Excluded	Included	Excluded	Included
log_expenditure	0.080***	0.042	-0.027	-0.047	-0.053	0.005
	(0.029)	(0.040)	(0.027)	(0.042)	----	----
logp_wheat	0.133***	0.132***	-0.135***	-0.138***	-0.002	0.006
	(0.022)	(0.018)	(0.021)	(0.019)	----	----
logp_sorghum	-0.086***	-0.075***	0.252***	0.256***	-0.166	-0.180
	(0.031)	(0.026)	(0.029)	(0.027)	----	----
logp_millet	-0.041*	-0.051**	-0.117***	-0.115***	0.158	0.166
	(0.022)	(0.020)	(0.021)	(0.020)	----	----
log_incidents	----	0.022***	----	-0.004	----	-0.019
	----	(0.009)	----	(0.01)	----	----
Constant	-0.443**	-0.143	0.875***	1.022**	----	----
	(0.216)	(0.308)	(0.206)	(0.319)	----	----
R-squared	0.550	0.712	0.644	0.723	----	----

Note: 1)* p<0.10, ** p<0.05, *** p<0.01

2) Values in the parentheses are the standard errors.

Expenditure coefficients (log_expenditure) measure the response of the $i-th$ commodity budget share to a 1% increase in real expenditures. Negative numbers imply necessary goods while positive ones indicate luxury goods. Thus, results in Table 11 suggest that wheat is a luxury without the “terrorist attack” variable. After we incorporate the terrorism variable, the wheat expenditure coefficient becomes insignificant and positive. The other expenditure coefficients are also statistically insignificant.

In general, the parameters relating to price effects are statistically significant at the 0.01 level. These parameters reflect the impacts of price on budget shares. Notice that we cannot conclude if two goods are complements or substitutes merely based on the sign of γ_{ij}, because of the mixed income and substitute effects. Thus, we need to employ the cross-price elasticity of demand instead. In other words, the inductive meaning of the price coefficients (γ_{ii}) is limited.

As expected, inclusion of the "terrorist attack" variable improves the goodness-of-fit as shown by the R-squared values. In addition, the coefficient of "terrorist attack" in the wheat equation is significantly positive, indicating that terror attacks do exert a positive effect on the budget share of wheat in Sudan. Intuitively, Sudanese probably tend to spend relatively more money on wheat once terrorist attacks break out, largely due to the increasing foreign aid of wheat. In contrast, terrorist attacks have negative but insignificant effects on the budget shares of sorghum or millet, which means it is possible that the outbreak of terrorist attacks reduces spending on sorghum and millet. However, this is not conclusive as such negative influences are not statistically significant.

The restrictions of economic theory are tested by standard asymptotic tests – likelihood ratio (LR) statistics derived from the estimates. The corresponding test statistics are reported in Table 12. As shown as follows, homogeneity (Equation (4.6)) alone, symmetry (Equation (4.7)) alone, and homogeneity & symmetry (Equation (4.6) & (4.7)) are not rejected for both AIDS models.

Table 12. Tests of Restrictions

	"terrorist attack" excluded			"terrorist attack" included		
Null Hypothesis	LR χ^2	df.	P-value	LR χ^2	df.	P-value
Homogeneity	2.36	2	0.3079	2.88	2	0.237
Symmetry	3.76	3	0.2884	5.71	3	0.1266
Homogeneity & Symmetry	3.76	3	0.2884	5.71	3	0.1266

Elasticities of demand derived from the AIDS models with and without terrorism included, with the restrictions imposed are presented in Table 13. Almost all the elasticities of demand are positive and statistically significant at the 0.01 significance level, implying that the expenditure shares for these cereal crops are sensitive to changes in total expenditure and the prices of three commodities.

Table 13. Elasticities Estimations

	Expenditure		Price					
			Wheat		Sorghum		Millet	
	Status of the "terrorist attack" Variable Inclusion							
	Exclude	Include	Exclude	Include	Exclude	Include	Exclude	Include
Wheat	1.378***	1.304***	-0.623***	-0.592***	-0.643***	-0.585***	-0.111*	-0.129**
	(0.068)	(0.101)	(0.069)	(0.063)	(0.081)	(0.084)	(0.058)	(0.056)
Sorghum	0.951***	0.953***	-0.214***	-0.205***	-0.513***	-0.540***	-0.224***	-0.209***
	(0.033)	(0.054)	(0.034)	(0.031)	(0.055)	(0.058)	(0.035)	(0.035)
Millet	0.471	0.597	0.056	-0.033	-0.527	-0.541	-0.001	-0.022
	----	----	----	----	----	----	----	----

Note: * p<0.10, ** p<0.05, *** p<0.01

The expenditure elasticities are expected to be positive. Expenditure elasticities for wheat in both models are greater than one (1.378 and 1.304), and are less than one for sorghum and millet. These magnitudes indicate that wheat is a luxury good in Sudan compared with sorghum and millet, regardless of the “terrorist attack” variable. The finding that the wheat expenditure elasticity exceeds one is consistent with our expectation since wheat is mainly perceived as the cereal for the generally wealthier people in the urban areas. In terms of terrorism we find a decline in expenditure elasticities particularly for wheat. Intuitively, when terror attacks occur, foreign organizations usually offer additional aid in the form of wheat or wheat flour, which explains a consumption increase but price decrease which likely explains the slight decline in the wheat expenditure elasticity in the model including terrorism. In terms of sorghum and millet, they are traditional staple commodities in Sudan. Therefore, it is not surprising that expenditure elasticities for them are less than one. Inclusion of the “terrorist attack” variable raises their expenditure elasticities. One possible explanation is that terrorist incidences lead to the shortage of sorghum or millet, and this further lifts the price of millet.

Own-price elasticities of demand for each cereal have the expected negative sign and are statistically significant at 0.01 levels, satisfying the well-acknowledged inverse relationship between price and quantity demanded. The signs of the cross-price elasticities for the three commodities are nearly all negative and statistically significant at the 0.01 levels. That is to say, they are complements, although they are believed to be substitutes with each other based on our knowledge of Sudan.

With regard to the effects of including terrorism, one other result is that we see the cross-price elasticity for millet and wheat changing sign with it moving from positive (substitute) to negative (complements). More generally, the estimated elasticities in Table 13 show slight differences in magnitude. For instance, the expenditure elasticity of wheat decreases while those for sorghum and millet increase. It is likely due to the increased wheat food aid and price changes stimulated by terrorist attacks.

Directed Acyclic Graphs (DAGs)

DAGs will avoid problems of potential endogenity and allow us to examine their dynamic interrelationship. We explore the relationships inherent in the time series data for the three major cereals and terrorism from 1967 to 2012. In the model, we consider relationships between seven variables: the prices for the three cereals and their corresponding consumption quantities, and the number of terrorism incidents. All estimations are conducted over the natural logarithms of the series.[28] Before implementing the DAGs, several tests are performed.

First of all, we examined stationarity of each time series (variable) as nonstationary items may compromise the statistical tests and can yield "spurious" regressions (Bessler and Kling 1984). To do this, we apply the Augmented Dickey-Fuller (ADF) test as explained in Harris (1995). We find we cannot reject the hypothesis that all variables are nonstationary (I (1)) at the 0.001 significance level.

The second step is to determine the optimal overall lag length (i.e., the same number of lags on each variable in the model building). This is determined using a likelihood ratio test (Hamilton, 1994):

[28] We obtain similar results if original format of data series are employed.

$$LR(j) = 2\{LL(j) - LL(j-1)\}; j = 0,1, \dots, J \tag{4.10}$$

$$LL(j) = -\frac{T}{2}\{ln|\Sigma_j| + Kln(2\pi) + K\} \tag{4.11}$$

where T is the number of observations; K is the number of equations; J is the maximum lags used in the system; Σ_j is the variance-covariance matrix of the innovations from vector autoregression (VAR) with *j* lags (VAR(*j*)); $LL(j)$ stands for the log likelihood for a VAR(*j*). The null hypothesis states that the parameter at lag *j* should be zero.

In this study, we will apply Hannan and Quinn loss function approach to specify the optimal lag length.

$$HQ = -2(LL(j)/T) + 2t_p \ln\{\ln(T)\}/T \tag{4.12}$$

where the notation has the same meaning with equation (4.11). Additionally, p^* is the total number of parameters in each equation.

As explained before, the maximum of lags in levels is set at four, and three for the first difference level, respectively (Wang and Bessler 2003). We find the fit criteria obtain their minimum when three lags are used. Nonetheless, due to the small size of our dataset (i.e., there are only 42 observations in total), a one period lag is imposed on the graphical models. Therefore, we consider the seven variables' current values and their corresponding one period lagged values for TETRAD search.

Then we import the whole dataset consisting of fourteen variables (i.e., seven current values and their one time period lagged values) into TETRAD V, only with time ordering constraints (i.e., the past may affect the future, but not vice versa). To determine the algorithm we use, Jarque-Bera normality tests are performed for each series. If the data follows a normal distribution, then the Jarque-Bera statistic satisfies a chi-squared distribution with two degrees of freedom. In addition, the Jarque-Bera test takes into account both the skewness and kurtosis.

Results indicate that sorghum price, millet price, the number of terrorist attacks, and their lagged values reject the null hypothesis of normality at a 0.000 significance level. Other series pass the normality test at the same significance level. Consequently, PC and GES algorithms are employed, albeit that the series aforementioned violate the normality assumption. Admittedly, the violation may make models approximate but still probably helpful (Akleman et al. 1999).

As suggested by Spirtes et al. (2000), we choose 0.2 as the alpha value for PC algorithm and the result is presented in Figure 6. To some extent, the graph is complicated with undirected, directed, and bi-directed edges. Still it indicates that the wheat consumption is connected with the terrorist attacks. Prices of the three commodities are interrelated with each other, while they are not that directly linked with their own consumption quantities. The only exception is the relationship between sorghum quantity and lagged sorghum price.

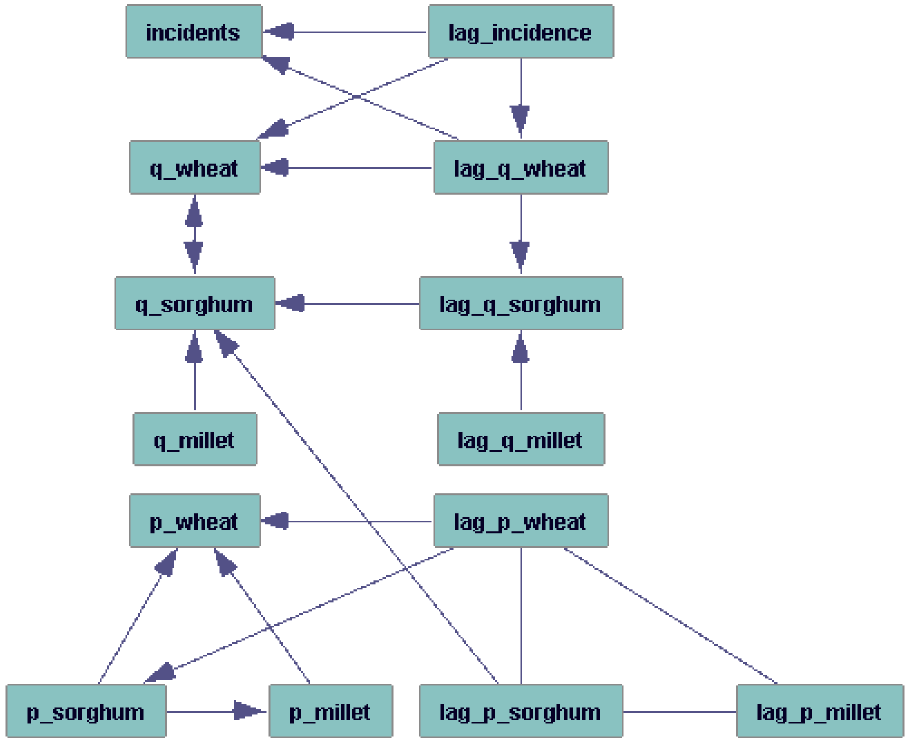

Figure 6. Pattern of Causal Flow among Wheat, Sorghum, Millet Price and Quantity, Terrorist Incidents, and Accordingly Lagged Ones Based on PC Algorithm

With respect to the GES result (Figure 7), the graph becomes simpler compared with the PC result in Figure 6. Two main conclusions remain: one is that wheat consumption is affected by terrorist attacks; another one is that three commodities' prices and consumption quantities are not directly linked.

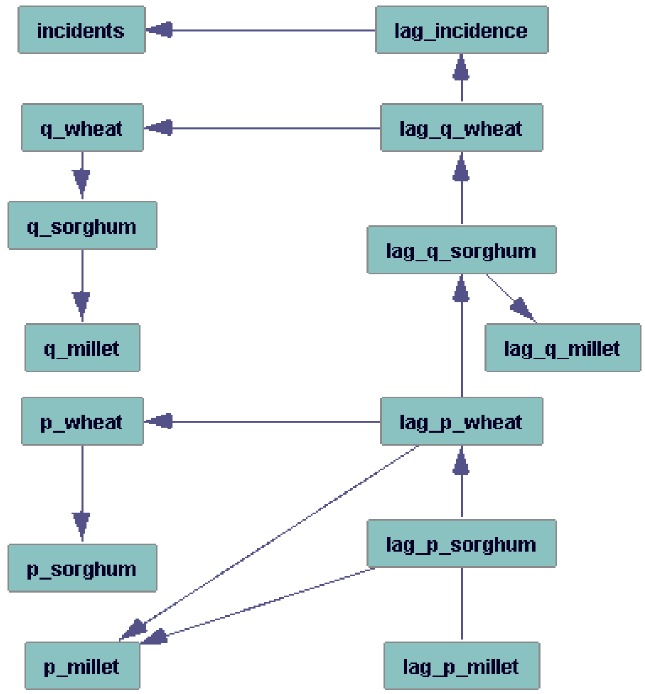

Figure 7. Pattern of Causal Flow among Wheat, Sorghum, Millet Price and Quantity, Terrorist Incidents, and Accordingly Lagged Ones Based on GES Algorithm

Several different specifications of variables were also analyzed with PC and GES algorithms, including the original and first differenced variables. In addition, we considered first differenced variables, lagged first differenced variables (with one time period), and lagged original variables. Under these alternatives, the graphs generated varied substantially, indicating that the conclusions derived from the graphs in Figure 6 and Figure 7 are not robust. Still, across all of these graphs we found some common characteristics. One is that the correlation between wheat consumption and terrorism remains regardless of the particular variable specification. The second one is that we find a weak linkage between own prices and consumption quantities. The third one is that three commodity prices are closely connected despite of disparate pathways, indicating that an endogeneity problem does exist in the traditional AIDS models.

Forecast Evaluation

Following the same estimation procedures described above, we analyze two AIDS models (i.e., AIDS model without any constraints, AIDS model with homogeneity and symmetry constraints) with seemingly unrelated regression model recursively covering from 1970 to 2000. Taking into account that to some extent terrorism could affect the cereal consumption in Sudan, we therefore incorporate the variable of terrorism into the AIDS models. To be consistent or to make sure the forecasts from different models are comparable, variables included in the DAG model are also commodity prices, expenditure, share, and terrorism, which are a little different from those investigated above. Specifically, take the model with wheat share for example. We start from the completely undirected graph consisting of wheat share, the total expenditure, the prices of wheat, sorghum, millet, and the number of terrorist attacks. Likewise, considering the sample size that is less than 100, we choose the 0.2 significance level to remove the edges and obtain the final DAG model – Figure 8. Only one undirected edges that were connected to the wheat share: wheat price (log formed). Nevertheless, we cannot identify the cause and effect. Therefore, we assume wheat share follows a random walk.

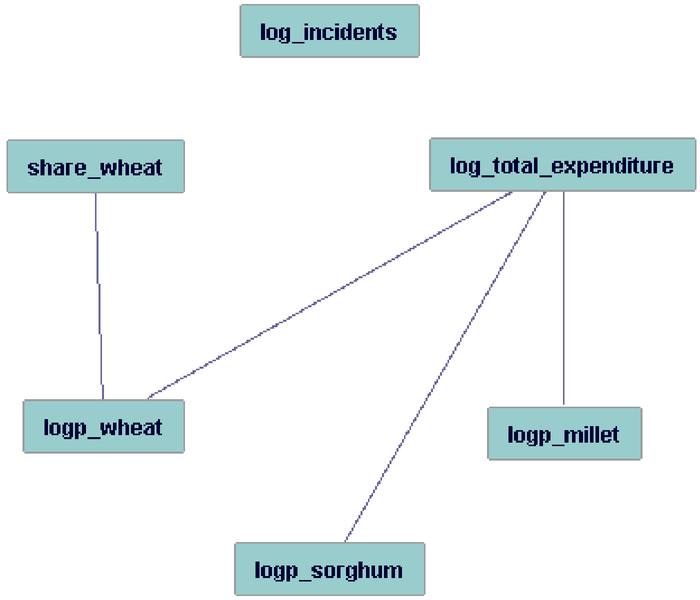

Figure 8. DAG for Wheat Share Equation: 1970 – 2000

Similarly, we implement the above procedures to other two equations (i.e., sorghum and millet) of the AIDS model iteratively. As a result, the final DAG models for forecasting are as follows. Wheat share series follows a random walk till 2007 while it is a function of terrorist attacks and wheat price since 2008. Both sorghum and millet share series are random walks from 2001 to 2012.[29]

Before generating forecasts of the three commodities' share based on the models estimated above, we need to obtain the forecasts of the contemporaneous variables on the right hand side of AIDS and DAG models (i.e., three commodities prices, total expenditure, and the number of terrorist attacks). Since all the series included here are

[29] Estimation results from AIDS and DAG are not presented here due to the space limitation, but they are available upon request.

I(1), thus we utilize a random walk model with drift to fit the data.[30] Then rested upon these forecasts and parameters estimated, we generate one-step-ahead and two-step-ahead forecasts for both AIDS and DAG models from 2001 to 2012 recursively. Following Wang and Bessler (2003), we evaluate the forecasted values for wheat, sorghum, and millet share on the basis of four criteria, involving equation-by-equation (i.e., mean square forecast error (MSFE) and mean absolute percentage error (MAPE)) and system standards (i.e., the log determinant and trace of forecast error matrix). Table 14 summarizes the results of the four criteria for three models' forecast performance.

Table 14. Forecast Performance on the Three Commodities Consumption Share

		One - Step				Two - Step			
Model	Commodity	MSFE	MAPE	Log(det)	Log(trace)	MSFE	MAPE	Log(det)	Log(trace)
AIDS	Wheat	0.049	2.085	-16.911	-4.111	0.050	2.134	-17.147	-4.227
	Sorghum	0.010	0.174			0.010	0.167		
	Millet	0.004	0.420			0.004	0.408		
AIDS with Constraints	Wheat	0.051	2.114	-16.755	-4.171	0.049	2.086	-16.988	-4.264
	Sorghum	0.009	0.165			0.009	0.164		
	Millet	0.003	0.361			0.004	0.381		
DAG	Wheat	0.037	1.789	-18.319	-4.873	0.032	1.699	-19.950	-5.346
	Sorghum	0.004	0.108			0.003	0.100		
	Millet	0.003	0.436			0.003	0.512		

Let's check the one-step-ahead forecasts first. With respect to MSFE, the DAG performs best for the three commodities' share forecast (i.e., it has the lowest MSFE value), followed by AIDS models. The two AIDS models' MSFE are quite close. We

[30] Here all the data series are logged transformed.

can derive similar conclusions under the MAPE standard, except for the millet share forecast where the AIDS with constraints produces the lowest MAPE (0.361). Apart from these equation-by-equation measurements, we also adopt two system-wide gauges. According to the log determinant of forecast error matrix, the DAG model (-18.319) appears to have better forecast accuracy compared with AIDS (-16.911) and AIDS with constraints (-16.755). However, the log trace of forecast error matrix does not account for the effects of covariance among the three commodities series (Wang and Bessler 2003). Therefore, the log trace suggests a slightly different ordering of models, whereas the DAG model still has the lowest log trace score (-4.873).

Given our small data size of forecast (i.e., 12 observations), we focus on one-step-ahead forecasts. Still, we present the two-step-ahead forecast results for comparison in Table 14. Likewise, most criteria suggest the superiority of the DAG model over the others. The only exception is the millet share forecast measured by MAPE. In addition, the rank of AIDS and AIDS with constraints models varies slightly with different standards. Thus, imposing theoretical constraints on models does not necessarily improve their forecast abilities.

Stepping forward to further access the forecast performance, Table 15 displays the encompassing regression results of the hypothesis that forecasts from one model encompasses forecasts from another model and vice versa. All the estimations were carried out in R with robust errors imposed to account for potential heteroscedasticity. Each row in Table 15 provides a test of the encompassing hypothesis.

Table 15. Encompassing Tests on One- and Two-Step-Ahead Forecasts of the Three Commodities Consumption Share

Step Ahead	Null Hypothesis		λ	p	Decision
1	AIDS encompasses AIDS_w	Wheat	-0.109	0.794	Fail to Reject
		Sorghum	5.144	0.046	Reject
		Millet	-0.109	0.794	Fail to Reject
1	AIDS_w encompasses AIDS	Wheat	1.109	0.021	Reject
		Sorghum	-4.144	0.097	Fail to Reject
		Millet	0.148	0.878	Fail to Reject
1	AIDS encompasses DAG	Wheat	0.771	0.118	Fail to Reject
		Sorghum	2.168	0.000	Reject
		Millet	1.284	0.013	Reject
1	DAG encompasses AIDS	Wheat	0.229	0.622	Fail to Reject
		Sorghum	-1.168	0.010	Reject
		Millet	-0.284	0.518	Fail to Reject
1	AIDS_W encompasses DAG	Wheat	1.217	0.016	Reject
		Sorghum	2.228	0.003	Reject
		Millet	1.323	0.179	Fail to Reject
1	DAG encompasses AIDS_w	Wheat	-0.217	0.617	Fail to Reject
		Sorghum	-1.228	0.057	Fail to Reject
		Millet	-0.323	0.731	Fail to Reject

Step Ahead	Null Hypothesis		λ	p	Decision
2	AIDS encompasses AIDS_w	Wheat	0.264	0.646	Fail to Reject
		Sorghum	2.929	0.321	Fail to Reject
		Millet	0.387	0.718	Fail to Reject
2	AIDS_w encompasses AIDS	Wheat	0.736	0.217	Fail to Reject
		Sorghum	-1.929	0.506	Fail to Reject
		Millet	0.613	0.570	Fail to Reject
2	AIDS encompasses DAG	Wheat	1.453	0.000	Reject
		Sorghum	1.453	0.000	Reject
		Millet	0.925	0.023	Reject
2	DAG encompasses AIDS	Wheat	0.161	0.755	Fail to Reject
		Sorghum	-0.453	0.061	Fail to Reject
		Millet	0.075	0.829	Fail to Reject
2	AIDS_W encompasses DAG	Wheat	1.052	0.048	Reject
		Sorghum	1.496	0.000	Reject
		Millet	0.979	0.079	Fail to Reject
2	DAG encompasses AIDS_w	Wheat	-0.052	0.912	Fail to Reject
		Sorghum	-0.496	0.080	Fail to Reject
		Millet	0.021	0.966	Fail to Reject

According to Table 15, we cannot draw a robust conclusion about which one is the encompassing or encompassed model at the 0.05 significance level, no matter for one- or two-step-ahead forecasts. In other words, the encompassing tests results indicate that a combination of the three models probably generate the most accurate forecasts. As a matter of fact, one significant advantage of combining forecasts is to learn the data generating process better and to achieve better forecasts (Granger and Ramanathan 1984).

In what follows, we proceed to estimate the optimal composite weights based on the forecasts from 2001 to 2012 with two methods herein. One way is to minimize the composite forecast variance subjected to the constraint that the sum of weights is equal to unity. Another approach is unrestricted ordinary least squares regression (Granger and Ramanathan 1984). That is, there are no restrictions on the weights while a constant item should be incorporated instead. The results of optimal weights estimated are summarized in Table 16.

Table 16. Optimal Weights of Forecasts

			Optimal Weight		
Method	Step	Commodity	AIDS	AIDS with Constraints	DAG
Traditional Method	1	wheat	0.471	-0.085	0.614
		sorghum	-0.665	0.197	1.468
		millet	0.396	-0.839	1.443
	2	wheat	0.282	-0.173	0.891
		sorghum	-0.205	-0.028	1.232
		millet	0.217	-0.423	1.206
Granger and Ramanathan	1	wheat	-0.064	-0.350	0.208
		sorghum	-1.590	1.164	0.449
		millet	-0.536	0.674	-0.197
	2	wheat	0.013	-0.057	0.047
		sorghum	-0.049	0.049	-0.948
		millet	0.103	0.196	-0.573

Apparently, different methods offer different combination strategies. For example, the traditional method always assigns a positive weight on the DAG model whereas it is not the case with the second method. Consequently, an out-of-sample evaluation of those composite forecasts is needed to access their forecast effectiveness. Nonetheless, data beyond the dataset in this paper are lacking. Hopefully, we may implement the evaluation process in the near future.[31]

[31] Additionally, an equal-weighted rule is another popular method for combined forecasts. Therefore, we also calculated the equal weights for the three models with OLS and then compare the results with the weights suggested by Granger and Ramanathan's (GR) method (**Error! Reference source not found.**). According to F test (or Wald test), we fail to reject the hypothesis that weights indicated by the two methods are statistically equal. In other words, equal-weighted and GR methods are statistically equivalent for composited forecast in our case. Therefore, we may choose equal weights unless we have robust evidence to hold other unequal weights (Armstrong 2001). Nevertheless, due to our modest sample size, we may still recommend the evaluation process.

Conclusion and Discussion

This paper explores the way terrorism affects cereal demand in Sudan applying classic AIDS models and an alternative way for modeling – DAGs. Additionally, the forecasts of the three cereal consumption shares by AIDS and DAG models are implemented. Several findings emerge.

First, we find an increase in terror attacks does not greatly affect consumers' behavior although we do see some changes in expenditure and price elasticities particularly for wheat. That elasticity increases, which is likely due to an increase in foreign aid providing low cost wheat after attacks which in turn increases consumption causing an increase in the budget share of wheat positively. Simultaneous sorghum and millet elasticities decrease reflecting a substitution of what for those commodities. Also the graphic models tentatively suggest that wheat consumption is related to the terrorist attacks and that wheat price is indirectly linked to terrorism in most graphs. Second we find wheat is a relatively luxury good while sorghum and millet are found to be necessities. This is consistent with the current situation of cereal market in Sudan. Third, all own-price elasticities have the expected negative signs showing downward sloping demand. Fourth, the cross-price elasticities are inconsistent with expectations: the results of both AIDS models indicate that the commodities are complements. Theoretically, the commodities should act as substitutes with each other. We feel the unexpected results probably originate from the validity of dataset as will be discussed later. Fourthly, we find that prices and consumption of the three cereals are not closely related to each other. Finally, the DAG model outperforms the AIDS models in forecasting the commodity consumption shares in most cases, while we cannot conclude that it is the encompassing model. We therefore suggest the combined forecasts from different models should be employed to achieve better forecasts.

Considering the conclusion of Chapter III, Chapter IV, and the current situation in Sudan, we propose that wheat is marginally affected by or affecting the terrorism (conflict) situation in Sudan. Chapter III suggests higher wheat prices cause more conflict events. However, Chapter III does not incorporate wheat consumption due to the unavailability of quantity data. In recent years, Sudan has been experiencing increasing wheat consumption and wheat food aid, with low levels of domestic wheat production. As a result, we propose that higher wheat price can affect wheat consumption and further induce terrorist attacks (conflicts).

On the basis of these wheat findings, we tentatively suggest that policy interventions mentioned in Chapter III, like introducing advanced and appropriate wheat production technology, could be implemented to improve Sudanese wheat production and this in turn may well help control wheat price and consumption, and further mitigate terrorist attacks. Likewise, other possible policy initiatives could involve lowering the imported wheat tariff or imposing subsidy.

There are many limitations that characterize this study, which could be improved in future research. First, the prices used in this paper are wholesale prices instead of retail prices, due to the huge difficulty of obtaining micro data in Sudan. Second, the time range of our yearly dataset is short compared with many other empirical studies. It is highly likely that these are the reasons why the three commodities indicate a complementary relationship in this study. Furthermore, we need to examine the accuracy of the combined forecasts beyond the range of the dataset we used. Therefore, there is a need for more valid and comprehensive datasets. Also, we may introduce subjective probability into the modeling with Bayesian techniques in the future studies.

Additionally our terror attack variable is limited and a richer specification might be introduced that considers, not only frequency, but also severity incorporating the number of dead or wounded in the attacks providing that data could be found.

Finally, alternative demand approaches could be used, such as the Inverse Almost Ideal Demand System (IAIDS) and Error Correction Model-Almost Ideal Demand System (ECM-AIDS), to further explore the cereal demand structure in Sudan.

CHAPTER V

CONCLUSIONS

This dissertation conducts analysis pertaining to causal factors and effects of conflict considering three main facets of the issue:

The effects of climate on conflict;

The causality between commodity prices and conflict;

The relationship among food prices, consumption, and terrorist attacks (one form of conflict).

In Chapter II (the first essay), I quantitatively explore the linkage between climate and conflict. In this effort I extend the current literature by carrying out a broad global and multi-year study considering both climate and other country-related characteristics. To achieve these objectives, I separated the dataset into two partitions for model estimation and validation, respectively. I then carried out estimation with both parametric and semiparametric techniques to unravel the link between climate and conflict. Subsequently I made predictions of conflict incidence. The results render robust evidence that a lower level of precipitation this year relative to last increases the probability of civil conflict. Additionally, I found that semiparametric models are superior out of sample predictors compared with parametric models.

Beyond the general cross-country research, it is indispensable and critical to perform case studies on conflict to understand causal factors and effects. Consequently, in Chapter III and Chapter IV, research is conducted on conditions in Sudan, an African country that has been beset by violent conflict for many decades.

Chapter III (the second essay) investigates the relationship between staple food prices (sorghum, millet, and wheat) and conflict events in Sudan. To do this, I utilized a time series SVAR model, allowing for asymmetric lag length structures plus innovation accounting techniques to depict the dynamic interaction among the variables of interest. The results indicate that the only significant linkage between food prices and conflict events in Sudan originates from the wheat market. Specifically, I find that, higher wheat prices lead to more conflict events, not vice versa. Moreover, this impact persists for almost two years after prices rise, even though it decreases over time.

Chapter IV (the third essay) examines the impacts of terrorism on demand for the three main cereals in Sudan. Both traditional AIDS models and a DAG are employed. In turn, I find terrorist attacks do not have a significant effect on consumers' behavior whereas they do impose some impacts on expenditure and price elasticities particularly for wheat. Analysis over the graphic models tentatively indicates that there exists a direct relationship between wheat consumption and terrorist attacks, and an indirect linkage between wheat price and terrorist attacks as well. In addition, I generate forecasts of the three commodities consumption shares using the AIDS and DAG models plus a composite of them, taking into account the effect of terrorist attacks. As a result, I find that combined combinations of the forecasts from those models could obtain better forecasts.

Now I discuss some limitations of this work which may be overcome in future studies.

The Chapter II analysis only identified a link between climate and conflict but not a specific mechanism, since I employed reduced-form methods. Considering the importance of understanding the climate-conflict pathway in policy design, it would be of interest for future research to address linkages more explicitly perhaps following suggestions in Burke et al. (2014).

In Chapter III, I had a limited data set and only included commodity prices and indicators on conflict events. Nevertheless, there are likely other determinants that may interact with those variables considered. For instance, South Sudan seceded from Sudan in July 2011. Thus it is entirely possible that food prices in Sudan could affect or be affected by those in South Sudan. Consequently, future work could extend the current work by enlarging the variety of causal factors in the dataset.

For Chapter IV, the analysis was limited by the short time period for which data were available, which in turn limits the robustness and validity of the results. Hence, datasets covering more time would be a useful extension in future studies. Moreover, subjective probability could also be taken into the account with Bayesian techniques.

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APPENDIX

Suppose precipitation R follows a normal distribution, with mean μ and standard deviation σ. Extreme events are defined as those values higher than b or lower than a, where $a < \mu < b$. Therefore, the probability of extreme events incident is:

$$P = 1 - P(a < R < b)$$

where

$$P(a < R < b) = P(\frac{a-\mu}{\sigma} < \frac{R-\mu}{\sigma} < \frac{b-\mu}{\sigma})$$

Denote

$$Y = \frac{R-\mu}{\sigma}$$

then Y follows a normal distribution, with mean 0 and standard distribution 1.

Thus,

$$P(a < R < b) = P\left(\frac{a-\mu}{\sigma} < Y < \frac{b-\mu}{\sigma}\right) = \int_{\frac{a-\mu}{\sigma}}^{\frac{b-\mu}{\sigma}} \frac{1}{\sqrt{2\pi}} e^{-\frac{y^2}{2}} dy$$

$$= \frac{1}{2}[erf\left(\frac{b-\mu}{\sqrt{2}\sigma}\right) - er\,f\left(\frac{a-\mu}{\sqrt{2}\sigma}\right)]$$

where $erf(\cdot)$ is usually called error function and defined as

$$er\,f(x) = \frac{2}{\sqrt{\pi}}\int_0^x e^{-t^2}\,dt$$

Thus, $erf(\cdot)$ is an increasing function.

When the standard deviation increases from σ to σ' (i.e., $\sigma < \sigma'$), the likelihood of extreme events incidents is

$$P' = 1 - P'(a < R < b)$$

where

$$P'(a < R < b) = P'(\frac{a-\mu}{\sigma'} < \frac{R-\mu}{\sigma'} < \frac{b-\mu}{\sigma'})$$

$$= \frac{1}{2}[erf\left(\frac{b-\mu}{\sqrt{2}\sigma'}\right) - er\,f\left(\frac{a-\mu}{\sqrt{2}\sigma'}\right)]$$

Thus, we have

$$P(a < R < b) > P'(a < R < b),$$

followed by

$$P < P'$$

That is, as the variability of precipitation increases, the probability of extreme events rises as well.